HELSINKI SCHOOL OF ECONOMICS

Department of Economics

CAUSALITIES IN THE STOCK MARKETS: COMPARISON OF THE U.S., JAPANESE AND FINNISH STOCK MARKETS

Master's Thesis in Econonomics

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ABSTRACT
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Objectives

The objective of this study is to examine the causalities in three different stock markets. Target is to find the most dominant market and find out how long the markets continue to affect each other's after the macroeconomic shock has occurred. In addition, this paper studies that is there noticeable differences in the market returns among the three nations. Integration of the markets has increased and it is interesting to find out which market provides the best financial benefits. The relation between the chosen three stock markets is examined over the whole examination period 31.12.1998 – 31.12.2007.

Data

The paper focuses on three different stock markets that are the New York, Tokyo and Finland Stock Exchanges. The three indices included in the analysis are Dow Jones Composite Average (USA), Nikkei 225 (Japan) and OMX Helsinki Cap (Finland). New York and Tokyo are the two biggest stock markets in the world. Helsinki is clearly the smallest of the three market places and is not globally important market area. Data is collected from Thomson Financial DataStream. Data includes over 2300 observations for each of the variables.

Results

The empirical results demonstrate that there exist cointegrating relationships among the selected stock indices. Granger-causality was very strong among the variables. Nikkei 225 and OMX Helsinki Cap performed similarly over the time period but Dow Jones Composite average volatility was more moderate. It could be seen that New York Stock Exchange was the most dominant of the three selected markets. Nikkei's growth rate was the slowest and volatility the highest and differed remarkably from the two other indices. Returns for a stock index were very poor during the studied time period.

Keywords

Stock markets, stationarity, cointegration, Granger-causality, vector autoregression

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KAUSAALISUUDET OSAKEMARKKINOILLA: VERTAILUSSA USA:N, JAPANIN JA SUOMEN OSAKEMARKKINAT

Tutkimuksen tavoitteet

Tämä tutkielma tarkastelee kausaalisuuksia ja relaatioita kolmen osakemarkkinan välillä. Tavoitteena on löytää dominoivin markkinapaikka ja tutkia kuinka pitkäkestoisia vaikutuksia osakemarkkinashokeilla on. Lisäksi tutkielmassa vertaillaan päivittäisiä tuottoja osakemarkkinoilta ja niiden vaihtelua maiden välillä. Markkinat ovat integroituneet yhä enemmän ja tavoitteena on löytää mikä markkina tarjoaa parhaan mahdollisen tuoton suhteutettuna riskiin. Vaikutussuhteita tutkitaan aikavälillä 31.12.1998-31.12.2007.

Data

Tutkielma keskittyy kolmeen markkinapaikkaan, jotka ovat New Yorkin, Tokion ja Helsingin pörssit. Jokaisesta pörssistä on valittu yksi indeksi ja valitut indeksit ovat Dow Jones Composite Average (USA), Nikkei 225 (Japani) ja OMX Helsinki Cap (Finland). New York ja Tokio ovat isoimmat pörssit maailmassa, kun verrataan listautuneiden yritysten markkina-arvoa ja Helsinki on selkeästi pienin valituista kolmesta markkinapaikasta. Data on kerätty Thomson Financial DataStreamista ja sisältää yli 2300 havaintoa jokaiselle muuttujalle.

Tulokset

Empiiriset tulokset osoittavat että valittujen indeksien välillä on voimakkaita relaatioita ja Granger-kausaalisuus on erittäin voimakasta. Nikkei 225 ja OMX Helsinki Cap käyttäytyivät samankaltaisesti tarkastelujakson aikana mutta Dow Jones Composite Averagen volatiliteetti oli selvästi pienempi. Tuloksista oli myös havaittavissa New Yorkin pörssin vahva vaikutus muihin alueisiin. Nikkein kasvuvauhti tarkastelujakson aikana oli heikoin ja samaan aikaan volatiliteetti oli suurin.

Avainsanat

Osakemarkkinat, stationaarisuus, yhteisintegraatio, Granger-kausaalisuus, VAR-menetelmä

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1. INTRODUCTION

1.1 Background

More open and global stock markets affect market behavior of the investors. The correlation of the national stock markets has increased over the time. Integration, for example, in the Nordic markets has increased during the recent years. Although there are still national share markets and indices in each of the Nordic countries, there are also indices that follow the general development in the Nordic markets. The reductions of the economic barriers between countries and standardization of the market instruments and technologies have increased cross-border trading. This paper aims to study how indices in different market places follow each other and how do the strongest markets guide smaller places like Helsinki Exchange or on the other hand is there even any noticeable comovements among different market places. Hatemi-J and Roca (2004) point out that there is still no conclusive evidence on the extent of integration between markets. There is a wide selection of literature that covers the subject but results vary depending on the theoretical framework, methodology, data and time period covered. Some studies have found that equity markets are integrated (for example, Eun and Resnick (1988), while others reported that equity markets are segmented (for example, Hiraki and Maberly (2000). Other discussion topic is which markets are significantly linked with each other. Results (Jorion 1989; Hatemi-J & Roca 2004) seem to show that there is some sort of linkage between certain groups that are connected through common factor, such as close regional, economic and geographical relationships. Jorion (1989) reported a strong linkage between European continental markets.

New York and Tokyo exchanges are the other two markets that I study in this paper. They are interesting marketplaces to study because of their size. For many years they have been ranked first and second in the world in terms of market capitalization (Hiraki and Maberly (2000)). Chinese market has increased its power during the recent years but New York and Tokyo are still considered the most significant markets. Helsinki and other Nordic exchanges are small stock exchanges when compared to these two giants and so they are not dominant in the global markets. However, one can ask whether the daily returns in Helsinki follow more Tokyo than New York or whether there is even any noticeable causality between Helsinki, Tokyo and New York.

1.2 Objectives

Research questions that are covered in this paper are:

- What are the relations between market indices in Helsinki, New York and Tokyo Exchange and is there causality in market reactions?
- How fast is the movement between stock markets and how much there is lag between markets?
- Is there anymore local markets and can one achieve the same financial benefit from any stock market?

The first question is studied in this paper by using vector auto regression (VAR) methodology which follows the Granger causality test. Granger causality might give misleading results when relationship involves three or more variables and in this paper three variables are studied. Also the second question is studied through VAR results and paper compares the Granger causes of the three markets and the existence and length of the lag between markets. In this paper I test two day lag in the VAR test which means that the t-1 and t-2 are being compared to the t-day value. Eun and Resnick (1988) noticed in their early study that markets reacted most strongly with a one day lag and most of the responses were completed within two days. Therefore, it is likely that there is no need to extend the lag beyond two days. Daily close values of the market indices from Tokyo, New York and Helsinki are used in this study to achieve accurate results about comovements and correlation. Data is collected from Thomson Financial DataStream.

I try to find answer to the third question with the help of growth rates and volatilities. I sum up those results to conclusions that were made with causality test. I study that is there any point to diversify the investments to different stock markets if markets are strongly involved and follow each other's movements. An important question is that are the financial benefits the same in all the stock markets? All the tests are made with statistical software Stata 10.

This paper starts in chapter 2 with literature review on the previous studies that have discussed about causalities and cointegration of the national stock markets. Also in chapter 2 is an overlook on some well-known asset pricing theories. This includes Capital Asset Pricing Model (CAPM) and arbitrage pricing theory. Furthermore, chapter 2 includes some thoughts about the investor psychology and behavior. Although this paper uses real values in the Granger causality test, the asset pricing theories cannot totally be ignored. The asset pricing theories provide valuable framework that explains why market prices should follow each other at least to some extent and how one could take advantage from misevaluation of the assets.

Chapter 3 concentrates on methodology that is critical in the studying of the causality and in the time series analysis. Chapter 3 covers topics such as stationarity, cointegration and Granger causality. Testing methods for these topics are explained in the end of the each section. This paper approaches Granger causality through vector autoregression (VAR) method, which offers suitable framework to causality studies.

In the chapter 4 the data is presented as well as the three stock exchanges (Helsinki, New York and Tokyo) that the data is collected from. I use three different indices in this paper. Those are Dow Jones Composite Average (USA), Nikkei 225 (Japan) and OMX Helsinki Cap (Finland) Included are some basic graphs that describe the price development of this indices during the recent years. I also compare OMX Helsinki Cap to the OMX Helsinki index to explain why I selected weight limited index instead an index which has no weight limitations.

Chapter 5 starts with basic statistics and comparison of the indices price development. In chapter 4 the indices are studied separately and the chapter concentrates to the comparison of the three indices. Basic statistics include comparison of the maximum and minimum values, daily returns and volatilities. After that the stationarity and cointegration of the indices is examined with Dickey-Fuller and Johansen test. VAR tests can be produced after the stationarity and cointegration has been confirmed. Tests are made with Stata 10 and results from Stata 10 are summed up in many figures and tables. All the output that has been created for this paper have been collected to appendix 1-3.

Chapter 6 sums up the conclusions from the empirical studies and links them to previous studies that were presented in literature review at chapter 2.

2. LITERATURE REVIEW

National stock markets and their relationships have been examined widely and from different points of view. Section 2.1 focuses on different approaches that there have been in the recent years. Studies that are covered in section 2.1 include results around the globe and different kind of stock market pairings. These pairings include Eastern and Western Europe, Chinese cluster and also U.S. and Japanese markets. Section 2.2 focuses to the most common asset pricing theories. Section 2.3 includes examples from studies that have focused on investor psychology and behavior. Theories in sections 2.2 and 2.3 should give basic knowledge on how the stock prices develop and why cointegration of the daily returns in different stock markets is probable.

2.1 Discussion on previous studies

In this section I review some studies that have focused on interactions between national markets. Macroeconomic news travel faster and faster around the globe and news from Asia and USA seem to have stronger impacts on the investors in, for example, Helsinki. This has motivated researchers to study the cointegration of the stock markets. Availability of data has also increased during the last decades and it has made the researching easier.

Eun and Resnick (1988) addressed mainly three issues in their research. They tried to find out:

(i) how much of the movements in one market can be explained by innovations in other markets,

(ii) does the U.S market influence other markets and

(iii) how rapidly the price movements affect other markets?

Data for their study was collected between 1980 and 1985.Their evidence showed that there is noticeable amount of corresponding among national stock markets. In average, innovations in the foreign markets account for about 26 percent of the error variance of a national stock market. U.S. stock market was found to be clearly the most influential market in the world and no other national stock market is even nearly as influential as the U.S. Vector autoregression (VAR) analysis showed that usually European and Asia-Pacific markets reacted most strongly with a one day lag to U.S. innovations. After that the responses diminished off and most of the responses were completed within two days.

Hatemi-J and Roca (2004) focused on Asian markets and examined relationships between China, Hong Kong, Singapore and Taiwan. Data was divided into two parts. The first sub-period was before the Asian financial crises of 1997 and included observation from January 1993 to July 1997. The second sub-period consisted of the time after the crises from January 1998 to September 10, 2001. Selected countries have common factors and Hatemi-J and Roca tried to find out how significantly common factors affect. Selected countries had significant level of trade between them and the Chinese culture associated all these countries. Chinese markets were also an economic powerhouse. They represented countries with very high economic growth rates and huge accumulated foreign exchange reserves. Although U.S. markets were not directly involved in the research, the results showed that U.S. effect was being transmitted by Singapore as the U.S. Granger-caused Singapore and so affected Hong Kong and Taiwan markets. U.S. and also Japanese markets were involved heavily in terms of trade and investments with Chinese markets. The results showed that relations in the Chinese market increased after the Asian crisis and affected in the later years Singapore. Also Singapore and Taiwan became more influential as they affected all the other markets. Hatemi-J and Roca pointed out that after the Chinese market's interdependency has increased, the potential diversification within this group of markets may not be attractive.

Hiraki and Maberly (2000) approached problem by studying Monday holiday closures in U.S. and how it affected Japanese equity returns. French (1980) noticed in an earlier study that U.S. market had so called U.S. –Monday effect which means that Monday's mean return has been negative and significantly different from other days of the week. In addition, French (1980) tested whether the systematically negative returns occur only on Monday or after any day that the market is closed. Results from the comparisons of the 'holiday' return and 'non-holiday' return indicated that negative expected returns were caused by a weekend effect and not by general 'closed-market' effect. Instead, in Tokyo Exchange Monday's mean return had not been unusual (Kato, 1991 and Ziemba, 1991), but Tuesday's mean return has been negative and differs statistically from other days of the week. Kato (1991) hypothesized that there was a cause and effect relationship between the U.S.-Monday and Japanese-Tuesday effects, but he did not conduct an empirical study to formally test this hypothesis. Hiraki's and Maberly's (2000) empirical evidences did not support Kato's (1991) hypothesis. Studies showed that Japanese Tuesday effect is more likely produced because of the institutional factors that are unique to Japan. Also they pointed out Japanese Tuesday effect is turning more and more to Japanese Monday effect and this supported the fact that institutional factors affected more to the market than the impact of the U.S. market. Hiraki and Maberly (2000) reminded that linkage between New York and Tokyo had strengthened during the analyzed time period.

Asprem (1989) focused on European stock markets in his paper and studied relationship between stock indices, asset portfolios and macroeconomic variables in ten European countries. Data in this study covered time between 1968 and 1984. One of the questions Asprem studied was whether U.S. stock prices have any influence on prices in the local European markets? By regressing national stock indices on current and past periods returns of the S&P 400 (Standard and Poor's industrial index) Asprem's results supported strongly the view that the American market or conditions influencing the American market were correlated with the local European markets. Although there were significant positive relationships between the S&P 400 and the local European markets, there was one exception in results, Finland. In Denmark, Norway and Sweden the results indicated that the stock prices may be predicted based on the last period's prices in the U.S. market but Asprem could not explain why Finnish market differed from other Nordic and European markets.

Comovements between the domestic intraday (or overnight) returns and foreign intraday returns of the US, UK and Japanese markets were tested by Connolly and Wang (2000). They included and controlled the potential effect of the macroeconomic news announcements for the period of 1985-1996. Empirical analysis showed that patterns of market return comovements occur. First, foreign intraday returns significantly and positively affected domestic market returns. Second, foreign market returns affected more profoundly domestic overnight returns than domestic intraday returns. Because domestic overnight returns preceded domestic intraday returns, it can be concluded that the domestic market processed the information contained in foreign market trading quickly and efficiently. Third, they found out that nearby foreign market exerts a greater impact on domestic intraday (overnight) market than the more distant foreign market and the preceding domestic overnight (intraday). In the empirical results the only exception was UK market, where the more distant US market had a greater influence than the nearby Japanese market. Fourth, domestic intraday markets tended to reverse returns realized in the preceding domestic overnight markets, whereas domestic overnight markets tended to display momentum relative to returns in the preceding domestic intraday markets.

Connolly and Wang (2000) studied also the impacts of the macroeconomic news. They found out that foreign economic news announcements have larger effects on domestic returns when the announcements are accompanied by large foreign market returns. Results suggested that the effect of macroeconomic announcements depended on the context in which investors interpreted the announcements and not just the news itself. Still the four distinct patterns of return comovements, which were introduced above, persist with essentially the same magnitude, even after controlling for the effect of macroeconomic news announcements. Also in each country the two foreign intraday returns are much more important than the lagged domestic market returns and all economic news announcements taken together in explaining the domestic intraday and overnight returns.

Égert and Kocenda (2007) compared Eastern and Western European stock markets and interdependence between them. Study included three Western European (Frankfurt, Paris and London) and three Eastern European (Budapest, Prague and Warsaw) stock markets. Study between Western and Eastern European markets offered good foundation to compare bigger and more developed markets against younger and smaller markets. Western markets are more mature and Eastern markets have started to develop over the last 10 years. Time range for the price data was between mid-2003 and early 2005. They estimated a VAR model that includes stock returns and stock market volatility. The VAR model is introduced in this paper in the chapter 3.5. Results didn't show any strong relationship for any of the stock index pairs, but apart from the lack of any stable long-term relation between the studied stock market indices, there were signs of short-term spillover effects both in terms of stock returns and stock price volatility. Granger causality tests showed the presence of bidirectional causality for returns as well as volatility series. Égert and Kocenda (2007) found spillover effects from returns to returns among the Eastern markets, among the Western markets and from Western Europe to Eastern Europe. However, no spillovers seemed to occur from the East to the West. Also volatility spillover effects were indicated between the same markets. Writers pointed out that this casted some doubt on the well-established position that only dominant markets could influence volatility on other markets. As conclusion, Égert's and Kocenda's research bore two implications. First, the finding that smaller market could impact dominant market shows that the Eastern European markets might be considered by hedge funds and institutional investors as a separate asset class as compared to stocks in Western Europe. Second, the finding of only short term but no robust long-term relationships between Eastern and Western European stock markets might have positive importance for international portfolio diversification into East Europe.

Causalities have also been studied from Finnish point of view and one recent study is made by Santti (2002). He studied comovements and causalities between Finnish and eight international equity markets and aimed to find out whether any economic value can be achieved in the Finnish equity market by first studying international equity market comovements and causalities. Correlation tests in Santti's studies showed that Finnish market comoves the most with Swedish, French and German equity markets and in Granger causality tests the Finnish market was found to be led by U.S., Hong Kong and Japanese markets. Also the results showed that correlations were stronger during the bear market than in the bull market. However, after heteroscedasticity adjustments were made the differences in the levels of correlation between the two cycles of the market disappeared. Santti found out that majority of the increase in correlations from bull to bear market was found to be related to increase in variances of the individual stock markets. The increased volatilities led to higher perceived comovements, while no actual increase in comovements was present.

Santti (2002) found out that Finnish intraday stock market returns were found to be predictable. The independent variable that possessed the highest explanatory power on the Finnish intraday stock market returns were found to be daily returns of the Hang Seng index, the heavy single day changes in NASDAQ and several days' returns of Dow Jones Industrial Average. With transaction cost of 0,3% included to test, two of the three active trading strategies outperformed the passive strategies, which showed that there could be potential economic value from the predictability in the Finnish stock market.

2.2 Asset pricing theories

Asset pricing theories bring theoretical approach to the shares prices. Although I study real prices in this paper, the asset pricing theories cannot be ignored. Asset pricing theories explain why price movements of the stocks should at least partially follow each other. I review couple of theories that are well-known and give good guideline on how the prices are formed in the markets. Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT) could be considered the most influential and widely used asset pricing theories. These are not the only asset pricing theories but especially APT explains why causality and cointegration should occur between stock exchanges. Also investor behavior cannot be brushed aside because there is always human aspect included in the markets and it offers different nuances to the markets. Investor psychology and behavior give aspect on why asset pricing theories are just guidelines and why asset prices differ from theoretically 'correct' prices.

2.2.1 Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) is used to determine the theoretically appropriate required rate of return for of an asset, if that asset is to be added to an already well-diversified portfolio, given that asset's non-diversifiable risk. It was developed by Sharpe (1964), Lintner (1965) and Mossin (1966) independently.

Formula for the CAPM is following:

$$E(R_a) = R_f + \beta_a(E(R_m) - R_f) \qquad (2.1)$$

where

$E(R_a)$ is the expected return on the capital asset

β_a is beta of the security

$E(R_m)$ is expected market return

R_f is risk free rate of interest

In this formula beta takes into account the asset's sensitivity to non-diversifiable risk also known as market risk. The difference between the expected market return and the risk free rate of interest is multiplied with beta. Hirshleifer (2001) points out that some studies have found incremental ability of beta to predict future returns after controlling for market value but some do not. Results depend on time, place, method, whether human capital is included in the market whether unconditional or conditional betas are used. Beta can also be presented in an alternative way

$$\beta_a = \frac{Cov(R_a R_m)}{\sigma_m^2} \tag{2.2}$$

The equation 2.2 implies that when covariance of the market and capital asset is known, beta can be calculated by dividing the covariance with market's volatility.

Bodie, Kane and Marcus (2001) write that CAPM is a statement about ex ante or expected returns, whereas in practice all anyone can observe directly are ex post or realized returns. In movement from ex ante to ex post analysis index model can be employed, whose excess return form is:

$$R_i = \alpha_i + \beta_i R_m + e_i \tag{2.3}$$

It can be shown that β_i equals CAPM beta. First one must derive the covariance between the returns on stock *i* and the market index. α_i is constant and can be dropped from the covariance terms because it has zero covariance with all the variables.

$$Cov(R_i R_m) = Cov(\beta_i R_m + e_i R_m) \tag{2.4}$$

$$Cov(R_i R_m) = \beta_i Cov(R_m R_m) + Cov(e_i R_m) \tag{2.5}$$

The firm specific or nonsystematic component is independent of the market wide or systematic component and so $\mathrm{Cov}(e_i R_m) = 0$. From this follows

$$\beta_i = \frac{\mathrm{Cov}(R_i R_m)}{\sigma_m^2} \tag{2.6}$$

This index model beta coefficient turns out to be the same as that of the CAPM expected return-beta relationship, but theoretical market portfolio of the CAPM is replaced with the well-specified and observable market index.

2.2.2 Arbitrage Pricing Theory

Other important model in the asset pricing is Arbitrage Pricing Theory (APT), which was initiated by economist Stephen Ross in 1976. APT could be considered as a supply side model and CAPM was more of a demand side model. CAPM gives the security market line, a relationship between expected return and risk as measured by beta. APT also stipulates a relationship between expected return and risk, but it uses different assumptions and techniques. Idea in the APT is that the price adjustment happens because imbalance in prices between two markets would lead to a possibility to make risk free profit. Arbitrage occurs when investor can construct a zero investment portfolio which will yield a sure profit. To construct a zero investment portfolio one must sell short at least a one asset and use the proceeds to purchase (go long on) one or more assets. Borrowing may be viewed as a short position in the risk-free asset. Any investor would like to take as large a position as possible in an arbitrage portfolio. (Bodie, Kane & Marcus, 2001) No-arbitrage condition occurs when securities are priced in a way that there are no risk-free arbitrage opportunities. Usually it is assumed that price relationships in the real-world markets satisfy no-arbitrage condition.

In APT there can be one or multiple systematic factors that affect security returns. A multifactor APT generalizes the single-factor model to accommodate several sources of systematic risk. Following model represents a case with two factors.

$$r_i = E(r_i) + \beta_{i1}F_1 + \beta_{i2}F_2 + e_i \tag{2.7}$$

where

E(r) is the expected return on stock

β_{ij} is the sensitivity of firm i to that factor F_j

F_j is the deviation of the common factor from its expected value

e_i is the firm specific disturbance

The e_i:s are uncorrelated among themselves and uncorrelated with the F_j factors. The factor model states that the actual return on firm *i* will equal its initially expected return and in addition a (zero expected value) random amount attributable to unanticipated economy wide events and another (expected zero value) random amount attributable to firm specific events. Macro factor F can represent for example departures of GDP growth from expectations or unanticipated inflation. F is always factor macroeconomic variable which affects the whole stock market.

One shortcoming of the multifactor APT is that it gives no guidance concerning the determination of the risk premiums on the factor portfolios. In contrast, the CAPM implies that the risk premium on the market is determined by the market's variance and the average degree of risk aversion across investors. As it turns out, the CAPM also has a multifactor generalization, sometimes called the intertemporal (ICAPM). This model provides some guidance concerning the risk premiums on the factor portfolios. Moreover, recent theoretical research has demonstrated that one may estimate an expected return–beta relationship even if the true factors or factor portfolios cannot be identified. (Bodie, Kane & Marcus, 2001)

2.3 Investor psychology and behavior

Movements in the stock markets and the consequences cannot only be considered through rational aspects, but it also requires some attention to human factors. It is often argued that markets must be assumed efficient unless conclusively proven otherwise and also there are forces that act to improve market efficiency. These investor psychology and behavior analyses can be traced to Adam Smith's analysis of "overweening conceit" and compensating wage differentials across professions, which described how individual psychology causes mispricing and inefficient resource allocation. This broader conception of economics has guided some finance researchers (Hirshleifer, 2001) and they have impugned market efficiency and based it upon theoretical arguments that the arbitrage forces acting to improve informational efficiency are not omnipotent. Kent, Hirshleifer and Teoh (2002) said that even some fans of the efficient market agreed that investors frequently make large errors. In their study they tried to prove that through the evidence of market prices that markets are subject to measurable and important mispricing. They argued that there is a good case for some minimally coercive and relatively low-cost measures to help investors make better choices and make the market more efficient. These involved regulation of disclosure by firms and by information intermediaries, financial reporting regulations, investment education and standardizations of the mutual fund advertising.

The strongest price changes may not have macroeconomic variables to support the fluctuation but more likely investors have reacted to the increased volatility and by buying/selling the assets increase the upward/downward movement. Strong negative or positive price pulse is a signal itself and investors make first reactions to this pulse and do not study immediately the theoretical and macroeconomic aspects that are creating price injection. This creates the market overreaction effect. Fair (2000) examined the largest five minute movements in the S&P 500 futures contract from 1982-1999, and found out that many of them have no clear associations with public news arrivals. Easton, Harris and Ohlsson (1992) noticed in their ten year time horizon studies that accounting measures can only explain approximately 60% of the variability of stock returns. Sequential information arrival hypothesis (SIAH) has been used for example by Darrat et al. (2007) and it argued that investors react to new information differently and the formation of new market equilibrium was not instantaneous and required some time and so created a lead-lag relation between volume and volatility.

Portfolio theory suggests that (apart from transaction costs) everyone should participate in all security markets, but some recent studies (Lewis, 1999 and Tesar & Werner, 1995) supported the view, that investors prefer domestic shares over the foreign ones. There is more localized bias within Finland (Grinblatt and Keloharju, 2001) and within the U.S. (Coval and Moskowitz, 1999). Investors are subject to a strong bias toward investing in stocks based in their home country and in their local region. Non-participation may derive from salience bias or from mere exposure (familiarity) effects (Hirchleifer, 2001). Mutual funds tend to invest locally, and earn higher returns on their local investments (Coval and Moskowitz, 2001), which is consistent with either rational processing of private information or with limited ability to process public information.

Seyhun (1990) found out in his studies focused on markets during and right after the crash that insiders purchased heavily after the crash and put more weight on the stocks that come down the most. Results are consistent with the assumptions that markets do overreact in crashes and in the other large stock price movements. Another paper that gives a view on investors' attitudes towards volatility is written by Andreassen and Krause (1990). They noticed that when exogenous prices fluctuate modestly investors prefer to buy on dips and sell on rises. But the behavior changes when stocks trend turns in a new course. Dips and rises guide investor behavior in the short time period but in the long run investors follow trends of the stock's price.

Hirshleifer (2001) wrote that further evidence from experience and from surveys show that real estate and stock market investors draw conclusions from trends when forecasting price movements. Behavior can be explained with example of a two-asset world. In this case an investor can either invest in a corporate stock or to government bond. The stock has higher return but at the same time is riskier. The bond, in the other hand, has smaller but much steadier return. During an economic boom the stock that offers high return is an attractive target for investor and so investor increase the risk of his/her portfolio by moving assets to the stock and at the same time decrease the weight of the bond. But when the expected return of the stock decrease during a recession, investors want less risky portfolio and move assets away from the stock market and so liquidity in the stock market decrease. Investor's portfolio is less risky but when all the investors follow the same curve, the upswings and downswings are steeper. Hirshleifer (2001) also argued that many or most familiar psychological biases, that cause systematic decision errors, can be viewed as outgrowths of heuristic simplification, self-deception and emotion-based judgments.

Darrat et al. (2007) studied the relationship between intraday trading volume and return volatility with and without identifiable public news. They argued that trading volume is significantly higher in the no-news periods and on the other hand analysis suggested that return volatility is higher in the period with public news. It appeared that overconfident investors overrated the precision of their private news signals and therefore traded too aggressively in the absence of public news and when the public news arrived investors' biased self-attribution triggered excessive return volatility.

After presenting previous studies, asset pricing theories and impacts of the investor psychology and behavior it is time to move on to the chapter 3 that covers the methodology for the empirical analysis of this study.

3. METHODOLOGY

On the third part of this paper the focus is on the methodology that is important for the empirical studies. Section 3.1 explains Gauss-Markov conditions, which should always be fulfilled in order to reach reliable results. Sections 3.2 and 3.3 focus on stationarity and cointegration. Also tests that enable results to study stationarity and cointegration are introduced in these two sections. Cointegration and stationarity are important concepts in order to study causality, which leads to last two sections of the methodology part. Granger-causality and Vector Auto Regression are introduced in section 3.4 and 3.5. First I explain Granger-causality, which helps to understand the idea behind Vector Auto Regression (VAR). Granger-causality test and VAR tests are similar tests but VAR produces more reliable results when more than two variables are involved.

3.1 Gauss-Markov conditions

Important part of the econometric modeling is Ordinary Least Square (OLS) regression which is strongly connected to VAR analyses. Following section does not concentrate on OLS regression that has been covered previously in many studies and is one of the foundations of the econometric studies but concentrates more on the Gauss-Markov conditions that should always be fulfilled in order to reach reliable results.

Properties of the regression coefficients depend critically on the properties of the disturbance term. To reach the best results in the OLS regression analysis following four conditions, which are known as Gauss-Markov conditions, should be satisfied. If the conditions are not satisfied, user should be aware of the fact and show extreme caution when analyzing the results and judge how seriously the results may have been affected. Presentation of the conditions follows Dougherty (2002).

Gauss-Markov condition 1: $E(u_i) = 0$ *for all observations*

The first condition is that the expected value of the disturbance term in any observation should be 0. It may vary between positive and negative values but it should not have systematic tendency in either direction.

If an intercept in is included in the regression equation, it is usually rational to presume that the first condition is satisfied automatically since the role of the intercept is to pick up any systematic but constant tendency in Y not accounted by the explanatory variables included in the regression equation.

Gauss-Markov condition 2: Population variance of u_i *constant for all observations*

The second condition is that all the population variance of the disturbance term should be constant for all observations. It may sometimes be higher or smaller but there should not be any priori reason for it to be more erratic in some observations than in the others. Because $E(u_i)$ is 0, the second condition can also be written

$$E(u_i^2) = \sigma_u^2 \text{ for all i.} \tag{3.1}$$

If this condition is not satisfied the OLS regression coefficients will be inefficient and more reliable results should be obtained with modification of the regression technique.

Gauss-Markov condition 3: u_i *distributed independently of* u_j $(i \neq j)$

The third condition states that there should be no systematic association between the values of the disturbance term in any two observations. In other words, the condition demands that disturbance terms are uncorrelated with each other and so the covariance between u_j and u_i is 0, because

$$\sigma_{u_i u_j} = E\big[(u_i - u_u)(u_j - u_u)\big]$$

$$= E(u_i u_j) = E(u_i)E(u_j) = 0 \quad (3.2)$$

In practice this means that if disturbance term is large and positive in one observation, there should be no tendency for it to be large and positive in the next one. If this condition is not satisfied, OLS will gain give inefficient estimates.

Gauss-Markov condition 4: u_i distributed independently of the explanatory variables

The final condition comes in two versions, weak and strong. The strong version is that the explanatory variables should be nonstochastic, which means that there are no random components. This is actually very unrealistic for economic variables and therefore weak version is commonly used. In the weak version the explanatory variables are allowed to have random components provided that they are distributed independently of the disturbance terms. If this is satisfied, it follows that $\sigma_{X_i u_i}$, the population covariance between the explanatory variable and the disturbance term is 0 and since the first Gauss-Markov condition is $E(u_i) = 0$ and the term involving X is nonstochastic it can stated that

$$\sigma_{X_i u_i} = E[\{X_i - E(X_i)\}\{u_i - \mu_u\}]$$

$$= (X_i - X_i)E(u_i) = 0 \quad (3.3)$$

In addition to these Gauss-Markov conditions it is usually assumed that the disturbance term is normally distributed. Reason for this is that if u is normally distributed, so will be the regression coefficients. The justification for the assumption depends on the Central Limit Theorem. The theorem states that if a random variable is the composite result of the effects of a large number of other random variables, it will have an approximately normal distribution even if its components do not, provided that none of them is dominant. The disturbance term is composed of a number of factors not appearing explicitly in the regression equation so, even if there is no knowledge about the distribution of these factors, it can be assumed that it is normally distributed. (Dougherty, 2002)

3.2 Stationarity

Straightforward definition of stationarity is that the mean, variance and autocorrelation structure do not change over time. Economic theories and tests require usually stationarity, because without it is impossible to achieve constant estimators. First with time-series it must be determined that is the data stationary or nonstationary. Easy way to find stationarity is to plot the data against time. When graph crosses the mean of the sample often then there is a good chance that the data is stationary.

It is possible to translate non-stationary time series in to stationarity with following technique.

$$Y_t = \Delta X_t = X_t - X_{t-1} \tag{3.4}$$

With above formula nonstationary term X_t turns in to Y_t, which is stationary term. In above formula the data is differenced once, but sometimes it is necessary to difference data twice or even higher order to reach stationary series, but orders that are higher than two are not often encountered in real data (Hall 1994, 14).

There have been controversial studies on whether the markets follow random walk model or whether they are at least to some degree predictable. Some believe that stock prices show some trends and changes showing whether the stock's price will rise or fall in the nearby future. Lo and MacKinlay (2002) tried to prove in their studies that random walk theory is wrong. Studies show small incremental changes throughout the years. In their conclusion they consider that stock market was in some point predictable which is against the random walk hypothesis. Random walk links to stationarity studies because it is one of the easiest examples of a nonstationary series.

$$x_{t+1} = \gamma x_t + \varepsilon \qquad (3.5)$$

In the equation 3.5 ε is the error term and γ is the coefficient. Stationarity can be tested with the standard Dickey-Fuller (DF) or the augmented Dickey-Fuller (ADF) test. The augmented Dickey-Fuller test is a version of the Dickey-Fuller test that is designed to test larger and more complicated sets of time series models. Basics for these tests are presented next.

Testing for nonstationarity

Method for testing nonstationarity is often described as testing for unit roots. Dickey-Fuller test is a standard test for a unit root presence in an autoregressive (AR) model. It was developed by D.A. Dickey and W.A. Fuller in the 1970s. Basics of the unit root testing is that if an I(1) time series becomes stationary upon being differentiated once (d=1), it must contain one unit root. Consider the simple AR(1) model with zero mean and error term of variance σ^2. We want to test if the unit root is present and so the null hypothesis of random walk is H_0: $\gamma = 1$. There are three main versions of the test and each version of the test has its own set of critical values:

(i) Test for a unit root (AR model),
(ii) test for a unit root with drift (AR model with constant) and
(iii) test for a unit root with drift around a stochastic trend (AR model with constant and time trend). (Greene 2000)

Following is an AR model with constant and time trend:

$$x_t = \beta_1 + \beta_2 x_{t-1} + \gamma t + \varepsilon. \qquad (3.6)$$

Equation (3.6) can be rewritten as

$$\Delta x_t = \beta_1 + (\beta_2 - 1)x_{t-1} + \gamma t + \varepsilon \tag{3.7}$$

where

$$\Delta x_t = x_t - x_{t-1}. \tag{3.8}$$

The series will be nonstationary if either the coefficient of x_{t-1} is 0 or the coefficient of t is nonzero. In the former case the series is difference-stationary, and in the latter trend-stationary. The test on the coefficient of x_{t-1} is one-tailed because a value of β_2 greater than 1 would imply an explosive process, which normally can be ruled out. Under the null hypothesis of nonstationarity, the *F*-test statistic does not have its usual distribution and the critical value is higher than that shown in the standard tables. Critical values for different samples are shown in Table 3.1. (Dougherty, 2002)

A requirement of the Dickey-Fuller test is that the disturbance term in the model should not be autocorrelated. If it is, further lagged values of x_t should be included on the right side of equation (3.6). When one or more lagged differences in x_t are included on the right side of the model, the test is known as the augmented Dickey-Fuller (ADF) test. (Dougherty, 2002)

ADF test is a version of the Dickey-Fuller test for a larger and more complicated set of time series models and ADF can accommodate higher order AR processes inε. Procedure for the ADF is the same as DF test but it is applied to the model which is presented by Dougherty (2002) as follows and the model including a constant and a time trend:

$$x_t = \beta_1 + \beta_2 x_{t-1} + \beta_3 x_{t-2} + \gamma t + \varepsilon \tag{3.9}$$

It can be shown that in this case the process will be nonstationary if $\beta_2 + \beta_3 = 1$ or if γ is nonzero. As with the DF test, also the ADF test is convenient to rewrite in the following form:

$$\Delta x_t = \beta_1 + (\beta_2 + \beta_3 - 1)x_{t-1} - \beta_3 \Delta x_{t-1} + \gamma t + \varepsilon. \quad (3.10)$$

With this equation null hypothesis H_0 that is tested equals $x_{t-1} = 0$. It should be noted that in practice the tests tends to have low power and a failure to reject the null hypothesis does not automatically mean that the series is nonstationary. In fact it is often impossible to distinguish between a nonstationary and a highly autocorrelated stationary AR process.

Greene (2000) represented counterparts to the critical F statistics for testing the null hypothesis. AR model, AR model with constant and AR model with constant and time trend represent the three main versions of the nonstationarity test. Below each model is four different probability levels and each probability level has critical F-value for four different sample sizes. AR model test is approved with 0,99 probability if F-value is below 2,16 (n=25). F-test is always one-sided so to approve the hypothesis the test value must be below the critical F-value.

Table 3.1 Critical values for the Dickey-Fuller test

	Sample size			
	25	50	100	∞
F ratio (D-F)	7,24	6,73	6,49	6,25
F ratio (standard)	3,42	3,20	3,10	3,00
AR model				
0,01	-2,66	-2,62	-2,60	-2,58
0,025	-2,26	-2,25	-2,24	-2,23
0,975	1,70	1,66	1,64	1,62
0,99	2,16	2,08	2,03	2,00
AR model with constant				
0,01	-3,75	-3,58	-3,51	-3,33
0,025	-3,33	-3,22	-3,17	-3,12
0,975	0,34	0,29	0,26	0,23
0,99	0,72	0,66	0,63	0,60
AR model with constant and time trend				
0,01	-4,38	-4,15	-4,04	-3,96
0,025	-3,95	-3,80	-3,69	-3,66
0,975	-0,50	-0,58	-0,62	-0,66
0,99	-0,15	-0,15	-0,28	-0,33

From Greene (2000 p.783)

3.3 Cointegration

Another important term in time series studies is cointegration. Time series of economic variables may seem to wander widely but still some pair of series may move so that their trends do not drift too far from each other. Examples might be long and short term interest rates and household incomes and expenditures. Cointegration analysis was introduced by Granger (1983). Engle and Granger (1987) formalized the cointegrating vector approach and wrote that similar idea arise from considering equilibrium relationships, where equilibrium is a stationary point characterized by forces which tend to push the economy back forward the equilibrium whenever it moves away. Economic variable is in equilibrium when the specific linear constraint

$$a'x_t = 0 \tag{3.11}$$

occurs and where x_t is determined as a vector of time series. But in most time periods x_t will not be in equilibrium and then quantity

$$\varepsilon_t = a'x_t \tag{3.12}$$

occurs and is known as the equilibrium error. Economy should prefer small value of the ε_t rather than a large value.

The following definition is taken from Engle and Granger (1987).

> *The components of the vector x_t are said to be cointegrated of order d, b, denoted $x_t \sim CI(d, b)$, if (i) all components of x_t are I(d); (ii) there exists a vector α $(\neq 0)$ so that $\varepsilon_t = a'x_t \sim I(d - b), b > 0$. The vector α is called the cointegrating vector.*

In a case where d=1, b=1, cointegration would mean that if components of x_t, were all I(1), then the equilibrium error would be I(0) and the error term ε_t will seldom drift far from zero mean and will frequently cross the zero line and so equilibrium will occasionally occur or at least close approximations are reached. If x_t was not cointegrated, then ε_t would wander widely and crossings of the zero mean would be very rare and in that case equilibrium concept has no practical implications.

There is close relationship between cointegration and error correcting models. Idea for error correction is that disequilibrium in one period is corrected in the next period. For example, the reasons to change in price in one period can be traced to previous period and may depend upon the degree of excess demand. Such scenarios can be derived as optimal behavior with sort of adjustments costs or incomplete information.

Testing for cointegration

Statistical program Stata 10 implements VAR- based cointegration test that is presented for example by Eun and Rosnick (1988). VAR of order p is considered:

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + Bx_t + e_t \tag{3.13}$$

where y_t is a k vector of nonstationary variables, x_t is a d vector of deterministic variables, $A_1, \dots, A_p$ and B are matrices of coefficients to be estimated and finally the e_t is a vector of forecast errors of the best linear predictor of y_t when using all the past y_p. By constuction e_t is uncorrelated with all the past y_p. If this is combined with the fact that e_t is also a linear combination of current and past y_t, e_t is serially uncorrelated. In empirical part I study indices from three national stock markets and so in this case y_t equals 3 x 1 column vector of daily rates of return of the three stock markets. Equation (3.13) shows that the right-hand side of the equation contains only constant and lagged values of each variable and the error term and so ordinary least squares (OLS) yields consistent estimates. The VAR may be rewritten as

$$\Delta y_t = \Pi y_{t-1} \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-1} + Bx_t + e_t \tag{3.14}$$

where

$$\Pi = \sum_{i=1}^{p-1} A_i - I, \Gamma_i = -\sum_{j=i+1}^{p-1} A_j \tag{3.15}$$

Granger's representation theorem states that if the coefficient matrix Π has reduced rank $r < k$, then there exist k x r matrices α and β each with a rank r such that $\beta' y_t$ is I(0). The number of cointegrating relations is presented by r and each column of β is the cointegrating vector.

3.4 Granger causality

The basic definition for Granger causality is quite simple. Following definition is based on writings of the creator of the Granger causality professor Clive Granger (1980, 2001).

In the beginning we have three terms, X_t, Y_t, and W_t and we first try to forecast X_{t+1} term by using the past terms of X_t and W_t. After that we try forecast X_{t+1} with X_t, Y_t, and W_t. Y appears to help forecast X_{t+1} if the second forecast is found to be more successful than the first test. Y might contain information that doesn't appear in past X or W. In particular, W_t could be a vector of possible explanatory variables. There are two conditions that must be fulfilled so that Y_t would "Granger cause" X_{t+1}:

(i) Y_t happens before X_{t+1} and

(ii) Y_t contains information useful in forecasting X_{t+1} that is not found in a group of other appropriate variables.

Naturally, the larger W_t is, and the more carefully its contents are selected, the more stringent a criterion Y_t is passing. Eventually, Y_t might seem to contain unique information about X_{t+1} that is not found in the other variables which is why the "causality" label is perhaps appropriate.

Time plays important part in causality definitions. One must be careful with timelines to make sure that the suspected causing term occurs before the effect and definitions in most theories lean strongly on that idea. Some implications are that it is possible for Y_t to cause X_{t+1} and for X_t to cause Y_{t+1}, a feedback stochastic system. However, it is not possible for a determinate process, such as an exponential trend, to be a cause or to be caused by another variable. (Granger 1980, Granger 2001)

3.5 Vector auto-regression methodology

Sims (1980) introduced Vector Auto Regression (VAR) into empirical economics and demonstrated that VAR offers a flexible framework for analyzing economic time series. Mathematically VAR can be represented as follows (Eun and Rosnick 1988):

$$y_t = \sum_{s=1}^{p} A_s y_{t-s} + C + e_t \tag{3.16}$$

where y_t is a k vector of nonstationary variables, x_t is a d vector of deterministic variables, $A_1, \ldots, A_p$ and C are respectively 3 x 1 and 3 x 3 matrices of coefficients, p is the lag length (2), and e_t is the 3 x 1 column vector of forecast errors of the best linear predictor of y_t using all past y_s. By construction, e_t is uncorrelated with all the past y_s. If this is combined with the fact that e_t is also linear combination of current and past y_t e_t is serially uncorrelated. The *i,j*:th component of A_s measures the direct effect that a change in the return to the *j*:th market would have on the *i*:th market in *p* periods

VARs have been used for two primary functions, which are

(i) testing Granger causality and
(ii) studying impulse response characteristics.

Equation system can be exceedingly large, it is, in fact a seemingly unrelated regressions model with identical regressors. As such, the equations should be estimated separately by OLS. The disturbance covariance matrix can then be estimated with average sums of squares or cross product of the least squares residuals. The proliferation of parameters in VARs is often cited as a major disadvantage of their use. (Greene, 2000)

When testing for Granger causality, tests of the restrictions can be based on simple F tests in the single equations of the VAR model. These tests can be based on the results of simple OLS estimates, because the unrestricted equations have identical regressors. The notion can be extended in a system of equations to attempt to ascertain if a given variable is weakly exogenous to the system. If lagged values of a variable y_t have no explanatory power for any of the variables in a system, then we would view y as weakly exogenous to the system. (Greene, 2000)

4. DATA AND TIME SERIES PROPERTIES

In the empirical part I compare how shocks on the share markets transfer around the globe. I have selected one index from three different exchange places. Bourses that I have selected are New York, Tokyo and Helsinki. Indices have been chosen so that they best describe the overall development of the markets. Indices differ in the various market places so I have tried to select as similar the indices as possible. The data is collected from Thomson Financial Datastream. Data includes daily closing prices for three market indices and the time period is between 31.12.1998-31.12.2007. Selected indices are Dow Jones Composite Average (U.S. market), Nikkei 225 Stock Average (Japanese market) and OMX Helsinki Cap (Finnish market). In section 4.1 I introduce the three indices and show summary statistics for them. With help of the summary statistics I justify the selection of the indices. In section 4.2 I compare the exchange places and analyze differences within them and compare the time-zones of the three stock exchanges.

4.1 Introduction of the indices

In section 4.1 I introduce all the three indices that are covered in this paper. These indices are Jow Jones Composite Average (DJCA), OMX Helsinki Cap (OMXHC) and Nikkei 225. All indices are price indexes so no cash dividend is reinvested in the index. I introduce them in the order of the market capitalization of the exchange place. First is the biggest exchange place New York and second in order is Tokyo. Helsinki is notably the smallest place and so OMXHC is introduced last. Daily returns that are in tables 4.1, 4.2 and 4.3 are not annualized daily returns but instead represent the change of the index's close values between t-1 and t.

Dow Jones Composite Average –index combines three different indices and includes all the corporations from the Dow Jones Industrial Average (30 companies), Dow Jones

Transportation Average (20) and Dow Jones Utility Average (15) indices. Number of the companies that are included in each index is inside the parentheses. Total amount of the corporations is 65 and most of the corporations have high market cap but the index includes also few medium cap and small cap corporations. Dow Jones Industrial Average is the most well known index and includes largest and most widely held public companies in the United States. The "industrial" portion of the name is largely historical because many of the companies have little to do with heavy industry. Companies that are included in the Dow Jones Transportation Average cover widely the transportation companies in the United States. The third index (DJUA) covers the utility companies. 56 of the 65 corporations are listed in the New York Exchange and the other nine corporations are listed in the NASDAQ. (NYSE Euronext)

In figure 4.1 is DJCA's value development for the last decade. Last four years the growth has been steady and during the last few months in 2007 volatility has increased. Highest value of the examination period was reached in the summer 2007.

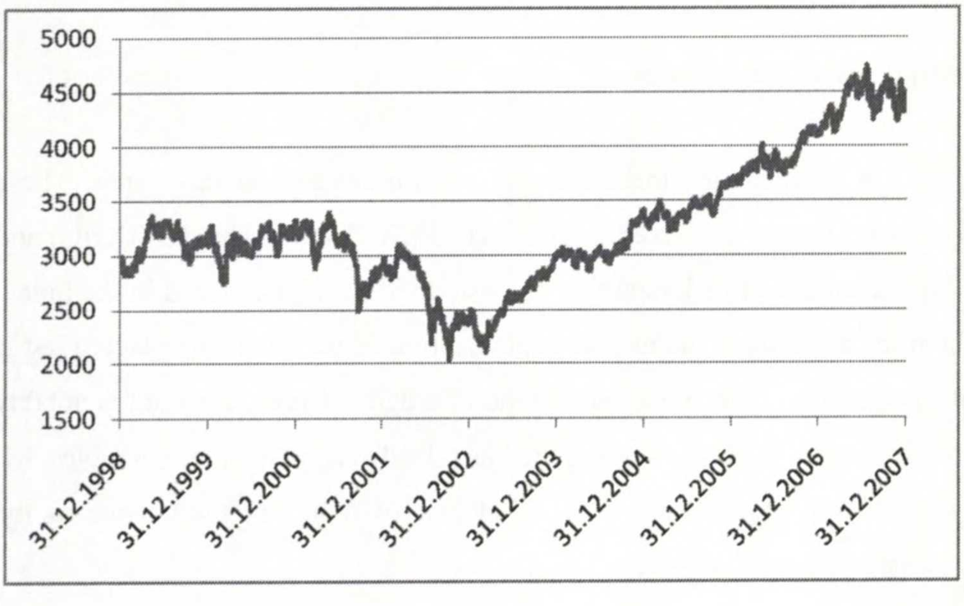

Figure 4.1 Dow Jones Composite Average 31.12.1998-31.12.2007

Table 4.1 includes basic statistics for the daily returns of the DJCA. The second column shows the critical values of the percentile limits. For example 95% of the values are above -0,01635 (-1,6%) and 90% of the values are between -1,6% and 1,6%. Third column shows the four smallest and the four largest values. The last column holds the number of observations, mean, standard deviation (volatility), variance, skewness and kurtosis. Skewness is a measure of the probability distribution of a real-valued random variable. When the value is zero or around it the data series is normally distributed. Kurtosis measures the peak of probability distribution and higher kurtosis means more of the variance is due to infrequent extreme deviations, as opposed to frequent modestly-sized deviations.

Table 4.1 DJCA statistics

	DJCA daily return summary			
	Percentiles	**Smallest**		
1 %	-0,02654	-0,07826		
5 %	-0,01635	-0,05335		
10 %	-0,01165	-0,04505	**Obs**	2348
25 %	-0,00534	-0,04107	**Sum of Wgt.**	2348
50 %	0,00009		**Mean**	0,00022
		Largest	**Std. Dev.**	0,01017
75 %	0,00572	0,04434		
90 %	0,01186	0,04712	**Variance**	0,00010
95 %	0,01576	0,05014	**Skewness**	-0,13812
99 %	0,02820	0,05491	**Kurtosis**	6,57517

Nikkei 225 has followed the trend of the Tokyo Exchange since 16.5.1949 and includes shares from 225 companies quoted in the Tokyo Exchange. List of the companies is updated once in a year. Nikkei 225 is the most watched index of Asian stocks. The Nikkei Average hit its all-time high (38 957,44) on December 29, 1989. Values on the

21st century dipped below quarter of the all-time high value early 2003 and recovered since then, without reaching the record levels. The Nikkei 225 is designed to reflect the overall market, so there is no specific weighting of industries. (Tokyo Stock Exchange)

In figure 4.2 is Nikkei's value development for the last decade. Fluctuation has been stronger and there hasn't been the same stability in the growth when compared to DJCA. Nikkei exceeded value of 20000 in the beginning of the year 2000 but after that hasn't been able to outrun those numbers.

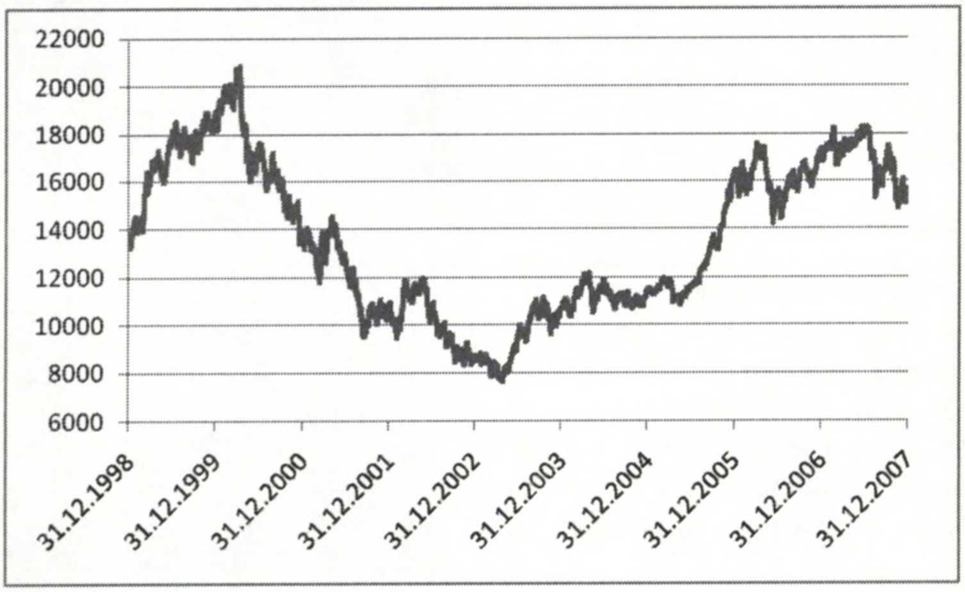

Figure 4.2 Nikkei 225 31.12.1998-31.12.2007

Table 4.2 follows the order of the table 4.1. When compared to DJCA, it can be seen that the variation of the Nikkei is bigger and the mean is smaller. 90% of the values are between -2,2% and 2,1%. Gap between the limiting values is over 1% bigger when compared to the critical values of the DJCA. Only DJCA's negative peek exceeds Nikkei's lowest value and in all the other cases Nikkei has wider dispersion.

Table 4.2 Nikkei statistics

Nikkei 225 daily return summary				
	Percentiles	**Smallest**		
1 %	-0,03363	-0,06979		
5 %	-0,02196	-0,06634		
10 %	-0,01638	-0,05417	**Obs**	2348
25 %	-0,00690	-0,05092	**Sum of Wgt.**	2348
50 %	0		**Mean**	0,00013
		Largest	**Std. Dev.**	0,01328
75 %	0,00742	0,04902		
90 %	0,01626	0,05010	**Variance**	0,00018
95 %	0,02110	0,05903	**Skewness**	-0,06598
99 %	0,03509	0,07489	**Kurtosis**	4,91251

OMX Helsinki All-Share Index (OMXH) includes all the shares that are listed on the Helsinki Stock Exchange. The index aims to reflect the current status and all the changes in the market. I have selected OMX Helsinki Cap (OMXHC) to be the third studied index, which is weight capped version of the OMXH. Maximum weight of one share is limited to 10% of total market value of the index. I have chosen OMXHC because Helsinki is relatively small market and so big firms like Nokia that are listed to Helsinki Stock Exchange won't affect so strongly to the market changes. The base date for OMXHC is 28.12.1990 with base value of 1000. (OMX Group)

In figure 4.3 is OMXHC's value development for the last decade. OMXHC's highest value was achieved in the beginning of the 2007. Ten year time period includes shrimps and booms. Examination period started with a fast growth which was followed by few recession years. Last four years have been strong upswing in the economy but there have also been few short negative periods.

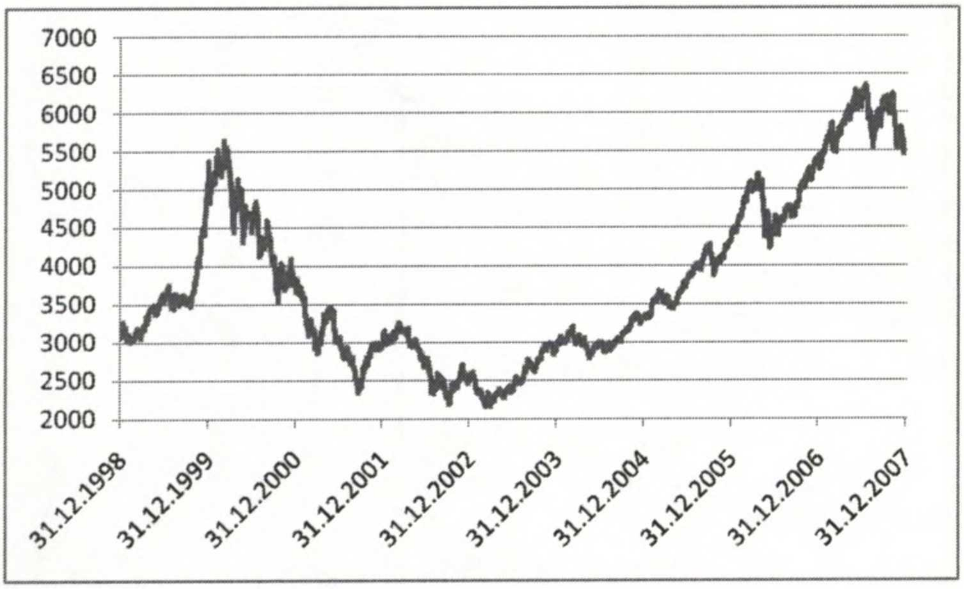

Figure 4.3 OMX Helsinki Cap 31.12.1998-31.12.2007

In table 4.3 is basic statistics for OMXH and OMXHC. Comparison of these two indices shows that OMXHC statistics are more in line with DJCA and Nikkei. Daily returns of the OMXH vary between -16 % and 16 % Maximum and minimum values of the OMXHC are only 5,8 % and -5,9 %. OMXH had the biggest drop on 27.07.2000 and the value came down 16 %. Reason for this huge drop was that on the same day Nokia published its second quarter result and Nokia's stock depreciated 21 %. (Kauppalehti.fi) OMXHC depreciated on 27.07.2000 only 4 % and that day wasn't even OMXHC's biggest depreciation day. On 05.01.2000 OMXHC came down almost 6 % because most of the stocks in Helsinki Exchange were depreciating. Also the standard deviation of the OMXH is almost two times bigger than OMXHC's and differs significantly from the two other indices. Weight limited index gives better view for the overall market movement in the small markets like Helsinki. 90 % of the OMXHC's values are between -1,9 % and 1,9 %, which is in line with DJCA's and Nikkei's 90 % critical values.

Table 4.3 OMXH and OMXHC statistics

OMXHC daily return summary					OMXH daily return summary				
	Percentiles	Smallest				Percentiles	Smallest		
1 %	-0.03323	-0.05923			1 %	-0,05459	-0,15973		
5 %	-0.01911	-0.05171			5 %	-0,03255	-0,15778		
10 %	-0.01362	-0.05005	Obs	2348	10 %	-0,02311	-0,08978	Obs	2348
25 %	-0.00560	-0.04867	Sum of Wgt.	2348	25 %	-0,00879	-0,08819	Sum of Wgt.	2348
50 %	0.00024		Mean	0,00033	50 %	0,00039		Mean	0,00053
		Largest	Std. Dev.	0,01187			Largest	Std. Dev.	0,02085
75 %	0.00682	0.05035			75 %	0,00962	0,08982		
90 %	0.01339	0.05201	Variance	0.00014	90 %	0,02281	0,09672	Variance	0,00043
95 %	0.01880	0.5823	Skewness	-0.12591	95 %	0,03441	0,10267	Skewness	-0,18682
99 %	0.032119	0.06882	Kurtosis	5,66803	99 %	0,05716	0,15677	Kurtosis	9,32913

4.2 Differences between the stock exchanges

Data that I use has been chosen from three different continents and also from three different time-zones. Exchange places are open in different times and Tokyo Exchange can react earlier to changes in New York Exchange than Helsinki. In Table 4.4 are all the opening hours translated into Helsinki's time-zone (GMT+2). All times are in winter time. Between last Sunday in March and last Sunday in October Tokyo's time change is +1 hour because daylight saving time isn't in use at Japan at the moment. Tokyo is fourteen hours ahead of New York and 7 hours ahead of Helsinki and trading sessions do not overlap with Helsinki and New York. Tokyo is also the first major market to begin trading each week. Helsinki and New York instead overlap opening times for few hours. There are also few differences between NYSE, TSE and OMXH. TSE is the only one from these three that has no market actions at noon. It is closed for 1,5 hour (local time 11.00-12.30). OMXH follows the common European standard in opening hours and is open Monday through Friday 8,5 hours per day. American exchange day is 2 hours shorter and for example OMX has used questionnaires recently about the possibility of achieving the same trading volume with opening hours following the American standard.

Table 4.4 Opening hours of the stock exchanges

Exchange	Time period From	To
Tokyo[1]	02.00	08.00
Helsinki	10.00	18.30
New York	16.30	23.00

Notes: Time is given in Helsinki timezone. Time is equal to GMT+2:00.

[1] Tokyo Stock exchange is closed between 04.00-05.30

In table 4.5 is some main factors from the three stock markets. Helsinki is in all aspects much smaller than New York and Tokyo. Market capitalization for the companies listed in Helsinki is only 2 % when compared to the companies that are listed in New York Exchange. Also, there is 20 times more companies listed in New York than in Helsinki. Also the biggest company in New York Exchange has bigger market cap than all the companies in the Helsinki Exchange together. Exxon was the biggest company in the New York Exchange in the end of 2007 and its market cap was 0,5 trillion dollars (NYSE Euronext) on that day which exceeds Helsinki's market cap by 100 billion dollars. There is no big difference in the number of listed companies between New York and Tokyo, but the market capitalization in New York is over three times bigger than in Tokyo. It can be concluded that the average size of the companies is smaller in Tokyo than in New York. Also in Helsinki the average size of the companies is bigger than in Tokyo.

Table 4.5 Basic numbers of the Stock Exchanges

	Market Cap in trillions ($)	Companies listed
New York	17,5	2767
Tokyo	4,7	2348
Helsinki	0,37	139

5. EMPIRICAL RESULTS

In this section, the Granger causalities for the whole examination period from 31.12.1998 to 31.12.2007 are estimated and discussed. In section 4 the indices were mostly analyzed separately and the validity of the indices were examined. In section 5.1 is summary of the basic statistics. These basic statistics include comparison of the daily returns and average growth rates. Daily returns are not annualized returns unless it is otherwise implied. Also the Dickey-Fuller test for unit root and Johansen test for cointegration are in section 5.1. Section 5.2 covers the VAR results for the whole examination period. In section 5.2.1 the relative values of the indices are tested. Section 5.2.2 concentrates on the daily returns of the indices. All the tests that include lag have lag of 2 because previous studies (Eun & Resnick, 1988) have showed that markets' reactions are strongest with a one day lag and most of the responses were completed within two days.

5.1 Basic statistics

Section 5.1 includes basic statistics for the three indices. Figure 5.1 represents all the three indices in the same figure with relative values to make the comparison easier. The sample period ranges from the 31st December 1998 to 31st of December 2007 and consist 2348 observations for each variable. Figure 5.1 describes the relative evolution of these three indices. For this figure the base values for the indices are the closing prices of 31.12.1998 which has been adjusted to 100. After that every close value has been adjusted to the base value so that the real daily returns don't change. Same base values make comparing of the indices easier and indices can be combined in one chart. OMXHC has had highest peaks during the time period. It should be noted that DJCA has more weight on large cap companies than the two other indices and, therefore, DJCA's moderate growth can be explained with that.

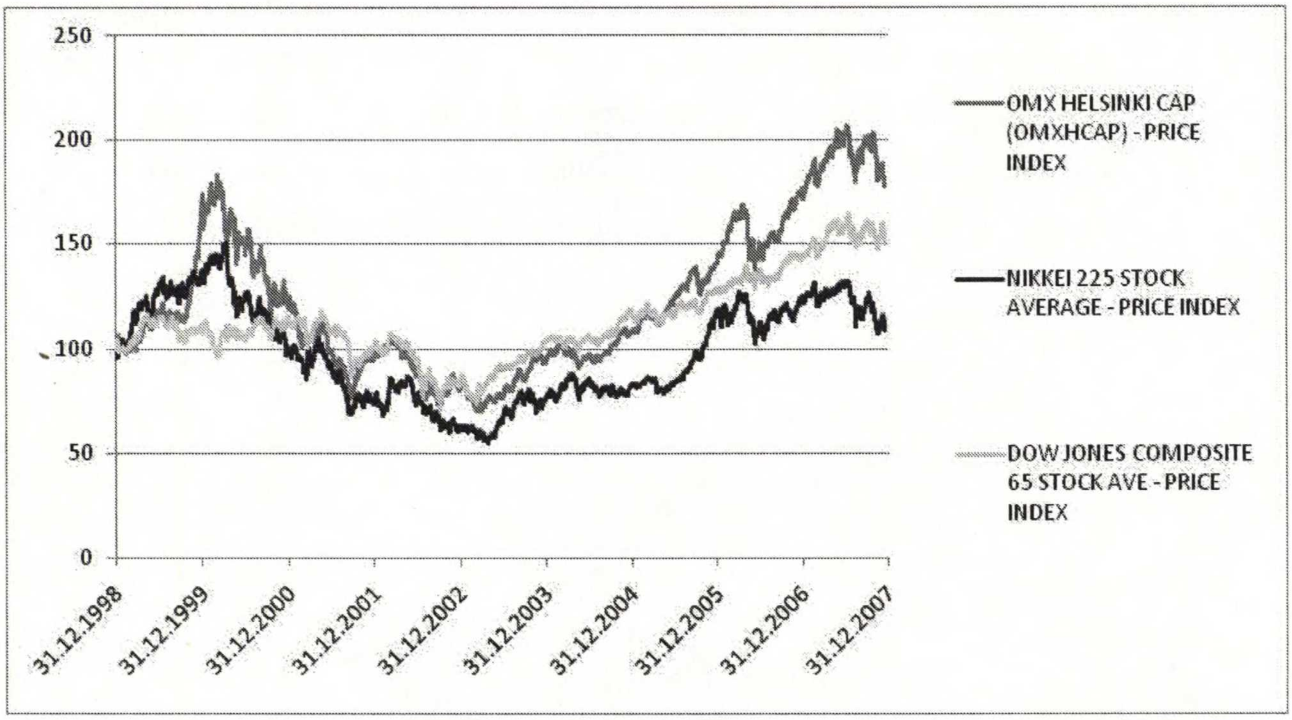

Figure 5.1 Relative development of the indices

Figure 5.1 points out that maybe DJCA is not the most suitable index to causality study. Because it has more weight on large cap companies, the daily changes are more moderate and results are not as reliable as they could be. It might diminish the Granger-causality effects of the New York exchange. Effect of this can be seen during the IT-'bubble' in year 2000 and also in the drop that occurred in 2004. Movement of the DJCA was more moderate during the 'bubble' because DJCA includes only few companies that were heavily impacted by this boom. Nikkei and OMXHC have clear peaks in the year 2000 but DJCA's price is quite constant and trend line flat. After the year 2000 peak both Nikkei and OMXHC have strong downtrend. Also DJCA follows the downtrend of the two other indices and for the next three years downward movement of the quotes continue. All three indices reach lowest quotes of the studied time period in the year 2003. Last four years of the time period the trend is upward. The growth of the OMXHC is strongest and Nikkei's growth is minor when compared to the two other indices. Between the years 2000 and 2004 DJCA and OMXHC follow each other closely but in the beginning of the year 2005 OMXHC's growth rate accelerates. OMXHC and DJCA reach highest values in the end of the time-period but Nikkei hasn't been able to recover from the slump that started after the IT-'boom'.

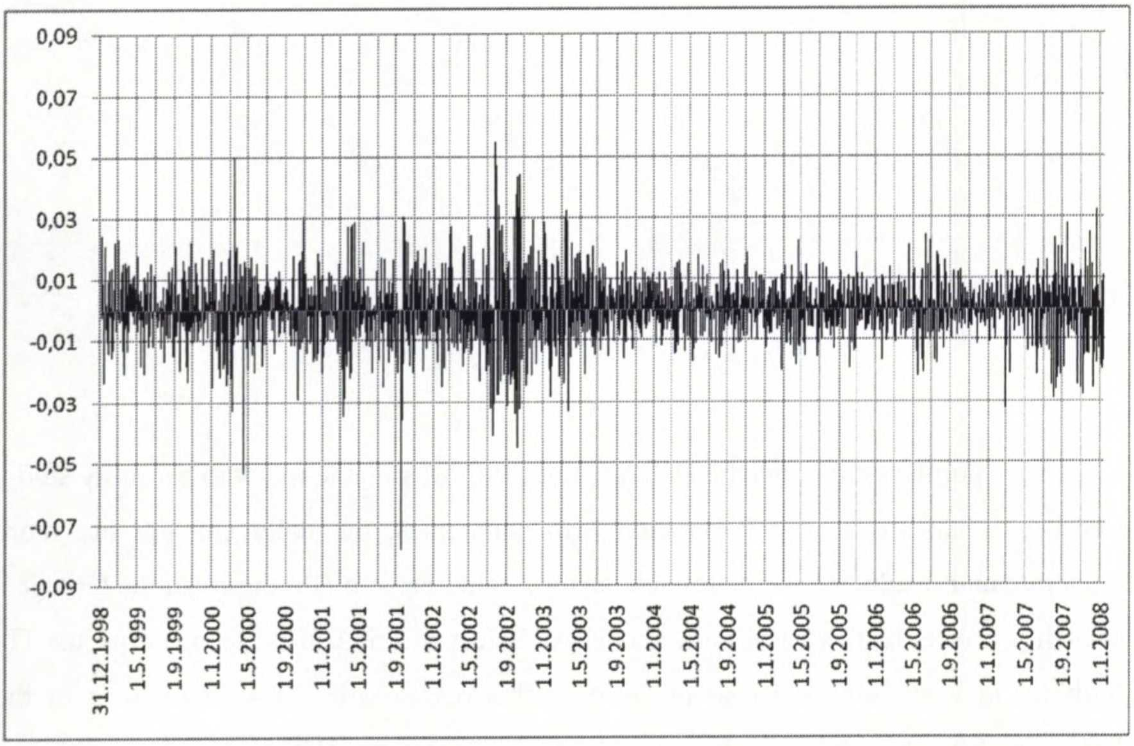

Figure 5.2 Logarithmic daily returns (Dow Jones)

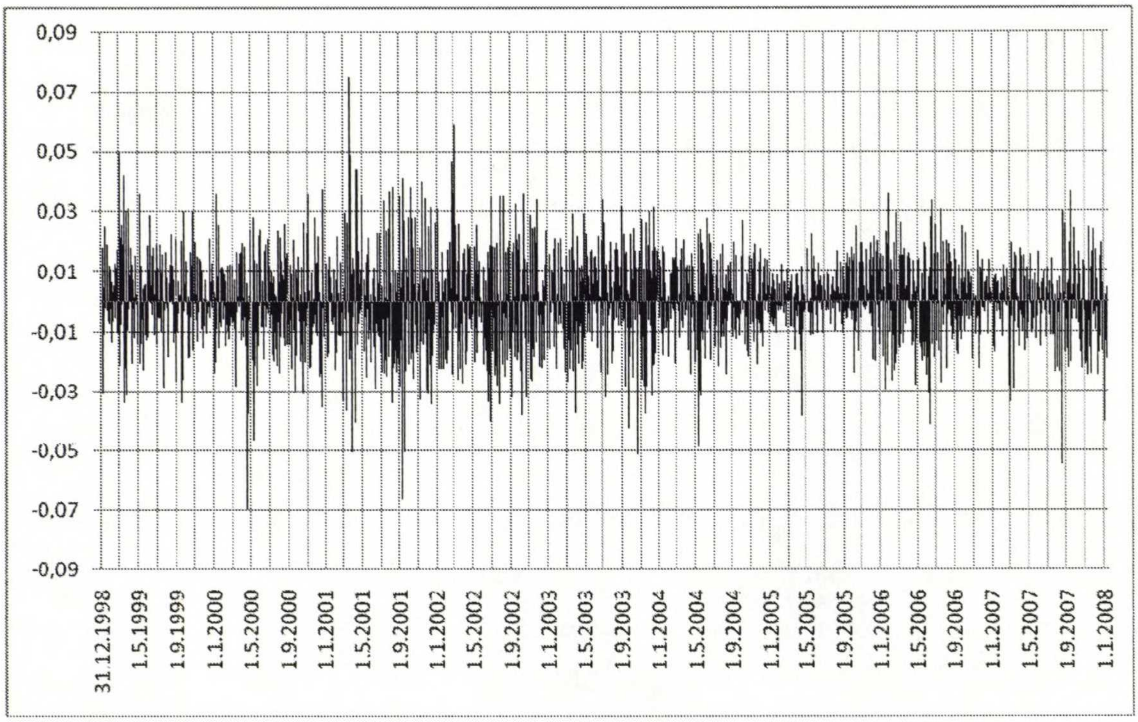

Figure 5.3 Logarithmic daily returns (Nikkei 225)

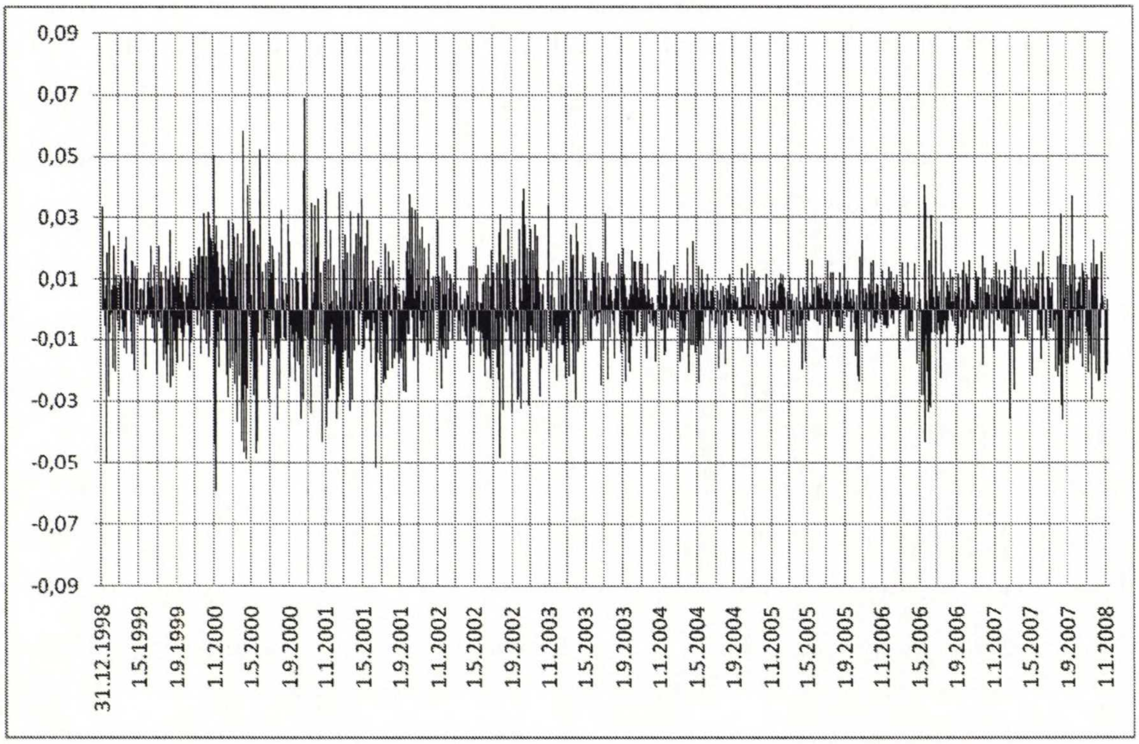

Figure 5.4 Logarithmic daily returns (OMX Helsinki Cap)

Figures 5.2, 5.3 and 5.4 show the daily returns for Nikkei 225, OMX Helsinki Cap and Dow Jones Composite Average. Changes of the DJCA have been moderate when compared to the other two indices. Usually the daily returns have circulated between +/- 2%. Nikkei 225 exceeds most often that limit and also in Nikkei's history there have been more negative daily returns than in OMXHC and DJCA history. Volatility of the daily returns has been largest from 2000 to 2003. Changes of the daily returns settle during the next years but accelerate again towards the end of the time period. Figures 5.1 and 5.3 show that Nikkei has the biggest volatility and the weakest growth rate.

Table 5.1 presents daily returns and standard deviations for the three indices. Results support the analyses that were made from the figures 5.1-5.4. Growth rate in the table 5.1 equals annualized return from the analyzed time period. Nikkei 225 annualized returns were worse than DJCA's and OMXHC's returns. Nikkei's growth rate is approximately 3,3 % and DJCA's annual return is 5,8%. OMXHC's return has been best during the last decade, around 8,2 %. Nikkei 225 has combined high volatility with poor returns during the last decade. Usually higher volatility links to higher returns which is the case between DJCA and OMXH. Although the growth rate of the DJCA is slower than OMXHC's, the moderate volatility balances the situation. Also the table 5.1 presents largest and smallest values of the indices during the time period. Max and min columns represent the highest and the lowest daily returns of the indices. Again in this case Nikkei 225 has biggest values in the both ends. Daily returns have alternated between -7 % and 7,5%. Maximum and minimum daily returns have exceeded the expected annual returns during the time period. It can be seen that the maximum and minimum daily returns are quite parallel during the examination period. Nikkei's combination of the low growth rate and high volatility don't offer attractive investment target. 21 % annual volatility for stock index is not remarkably high but it should provide much higher growth rate than 1,2 % to be an attractive investment. DJCA seems to be the steadiest index which is in line with the fact that the index includes mainly the largest and widely held public companies in the United States.

Table 5.1 Annual statistics summary

Summary statistics

	Growth rate	Volatility	Min	Max
Nikkei	1,18 %	21,08 %	-6,98 %	7,49 %
OMXHC	9,14 %	18,84 %	-5,92 %	6,88 %
DJCA	5,90 %	16,14 %	-7,82 %	5,49 %

5.1.1 Testing for nonstationarity

Augmented Dickey-Fuller test must be performed to ensure the stationary of the data. Results for the unit root test are in table 5.2. First there are results for the relative values of the indices and after that the results for the daily returns. In "Test Statistic" –column is the value for each of the studied indices. Second column is dedicated for coefficient value and the last columns represent the critical values of the test for three different probability levels. Under the null hypothesis of nonstationarity, critical value of t at the 10 percent level is -3,12 and hence the null hypothesis of nonstationarity is not rejected for the relative values of the indices. Test statistic for relative values is significantly above the critical t-values. It can be seen that the coefficients of the daily returns is around -1 and t statistic significantly below the critical values. That allows the null hypothesis of nonstationarity to be rejected at the 1 percent level.

Table 5.2 Test for unit root

Augmented Dickey-Fuller test for unit root Number of Obs = 2345

	Test Statistic	**Coefficient**	*Interpolated Dickey-Fuller 1% Critical Value*	*5%Critical Value*	*10% Critical Value*
Relative values			-3,96	-3,41	-3,12
DJCA	**-1,502**	**-0,001**			
Nikkei	**-1,241**	**-0,001**			
OMXHC	**-1,043**	**-0,002**			
Daily returns			-3,96	-3,41	-3,12
DJCA	**-27,754**	**-0,962**			
Nikkei	**-28,274**	**-1,033**			
OMXHC	**-27,944**	**-1,020**			

5.1.2 Testing for cointegration

Johansen test has been used to test cointegration of the daily returns. Table 5.3 sums up results that are collected from Stata 10. Results include all the three analyzed indices. Trace statistics can be compared to 5% critical values that are clearly exceeded. Conclusion from the table is that there exists cointegrating vector for the daily returns. Trace statistic test indicated three cointegrating vectors among the variables with a 1% rejection level. Trace statistics values are high and indicate high cointegration among the variables.

Table 5.3 Cointegration test for daily returns

Johansen tests for cointegration

Number of obs = 2346

Lags = 2

maximum rank	*parms*	*LL*	*eigenvalue*	*trace statistic*	*5 % critical value*	*1 % critical value*
0	12	20306,63	.	3078,032	29,68	35,65
1	17	20903,67	0,39889	1883,956	15,41	20,04
2	20	21443,61	0,36891	804,0721	3,76	6,65
3	21	21845,64	0,29018			

5.2 Vector Auto Regression

5.2.1 Vector Auto Regression for the relative values

In this section I analyze the VAR results for the relative values of the indices. The base values for the indices are the closing price of 31.12.1998 which has been adjusted to 100. In table 5.4 is VAR results with two day lags. Three indices are separated into three columns. First row indicates the index on which the comparison is made. First column compares all the indices to Nikkei 225. Second column compares indices to the OMXHC and the third compares the causality of the indices to the Dow Jones Composite average. "Lag t-1" and "Lag t-2" are the t-1 and t-2 values of the indices and "z" is the z-value of the VAR test. "P>|z|" is the probability that the lagged value is Granger causing the index. If the "P>|z|" value is below 0,05, there is 95% probability that there is interdependence between the compared indices.

Table 5.4 is divided in to three sections. In the first section are VAR test results for Nikkei t0 values. Results in the first section show how Nikkei is affected by the lagged values of the Nikkei, OMXHC and DJCA. For example, Nikkei's "Lag t-1" line shows that can Nikkei's t-1 value explain Nikkei's t0 value. OMXHC's "Lag t-2" line shows that can OMXHC's t-2 value be explaining factor for Nikkei's t0 value. Both probabilities are 0,000 which indicates that Nikkei's t-1 and OMXHC's t-2 values cannot be excluded from equation and most likely Granger cause Nikkei's t0 value. Second and third sections include results for OMXHC and DJCA. The other two sections follow the same logic than in the first section.

Table 5.4 shows that DJCA and OMXHC seem to Granger cause Nikkei's values and there seems to be almost the same situation with OMXHC. Only OMXHC's t-2 value does not seem to cause the t-day value. But Nikkei and OMXHC do not seem to cause DJCA's values but it should be noticed that there is no time-adjustments in the table 5.4. Because of the time-zone differences investors in the New York Exchange can react to the t0 value of Nikkei 225 and OMX Helsinki Cap.

Table 5.4 VAR results

Vector autoregression results

Nikkei (t0)	**z**	**P>|z|**	**OMXHC (t0)**	**z**	**P>|z|**	**DJCA (t0)**	**z**	**P>|z|**
Nikkei			*Nikkei*			*Nikkei*		
Lag t-1	44,65	0,000	Lag t-1	-3,78	0,000	Lag t-1	-1,64	0,101
Lag t-2	5,00	0,000	Lag t-2	3,94	0,000	Lag t-2	1,57	0,116
OMXHC			*OMXHC*			*OMXHC*		
Lag t-1	8,91	0,000	Lag t-1	45,44	0,000	Lag t-1	-1,74	0,082
Lag t-2	-8,91	0,000	Lag t-2	1,59	0,112	Lag t-2	1,90	0,058
DJCA			*DJCA*			*DJCA*		
Lag t-1	14,83	0,000	Lag t-1	17,07	0,000	Lag t-1	46,35	0,000
Lag t-2	-14,77	0,000	Lag t-2	-16,81	0,000	Lag t-2	0,18	0,859

The data has been adjusted in the table 5.5 so that the "Lag t-1" and "Lag t-2" values of the OMXHC and Nikkei are actually t0 and t-1 values. Nikkei's t0 value occurs before the OMXHC's and DJCA's t0 values and OMXHC's t0 value occurs before the DJCA's t0 value. The time-zone differences for three exchange places were shown in the table 4.4. The adjustment affects to the Granger causality and strengthens all the causalities. It seems that the movement of the relative values is similar in all the situations and all the indices interact with each other.

Table 5.5 Time-zone adjusted VAR results

Vector autoregression results Modified with time-zones

Nikkei (t0)	**z**	**P>|z|**	**OMXHC (t0)**	**z**	**P>|z|**	**DJCA (t0)**	**z**	**P>|z|**
OMXHC			*Nikkei*			*Nikkei*		
Lag t-1	8,91	0,000	Lag t-1	11,79	0,000	Lag t-1	5,62	0,000
Lag t-2	-8,91	0,000	Lag t-2	-11,59	0,000	Lag t-2	-5,67	0,000
DJCA			*DJCA*			*OMXHC*		
Lag t-1	14,83	0,000	Lag t-1	17,07	0,000	Lag t-1	14,01	0,000
Lag t-2	-14,77	0,000	Lag t-2	-16,81	0,000	Lag t-2	-13,76	0,000

5.2.2 Vector Auto Regression for the daily returns

In this section I analyze the VAR result for the daily returns. Tables 5.6 and 5.7 follow the same logic than tables 5.4 and 5.5. The difference is that results represent the VAR of the daily returns. It can be seen that the causality with the daily returns is not so strong and especially the "Lag t-2" values don't seem to cause the t0 values.

Table 5.6 VAR results

Vector autoregression results for daily returns

Nikkei (t0)	z	P>|z|	OMXHC (t0)	z	P>|z|	DJCA (t0)	z	P>|z|
Nikkei			*Nikkei*			*Nikkei*		
Lag t-1	-5,54	0,000	Lag t-1	-4,34	0,000	Lag t-1	-2,12	0,034
Lag t-2	-0,61	0,541	Lag t-2	-0,79	0,431	Lag t-2	0,60	0,550
OMXHC			*OMXHC*			*OMXHC*		
Lag t-1	8,58	0,000	Lag t-1	-2,11	0,035	Lag t-1	-0,49	0,623
Lag t-2	2,44	0,015	Lag t-2	2,05	0,040	Lag t-2	1,14	0,254
DJCA			*DJCA*			*DJCA*		
Lag t-1	14,22	0,000	Lag t-1	17,87	0,000	Lag t-1	-0,24	0,812
Lag t-2	-1,05	0,292	Lag t-2	1,04	0,299	Lag t-2	-0,61	0,545

The time-zone adjustments have been made to the table 5.7 and like in table 5.5 also in this situation time-zone adjustments increase the Granger causality of the indices. All the "Lag t-1" values apparently cause t0 values but causality between "Lag t-1" and "Lag t-2" values is much weaker. Only Nikkei's and OMXHC's "Lag t-2" values seem to have some causality with each other's t0 values. Results are in order with the previous studies and indicate strong relations among the selected countries. Égert and Kocenda (2002) found out bidirectional causalities among the Western and Eastern European markets that are in line with the findings in this paper.

Table 5.7 Time-zone adjusted VAR results

Vector autoregression results for daily returns Modified with time-zones

Nikkei (t0)	z	P>|z|	OMXHC (t0)	z	P>|z|	DJCA (t0)	z	P>|z|
OMXHC			*Nikkei*			*Nikkei*		
Lag t-1	8,58	0,000	Lag t-1	11,49	0,000	Lag t-1	6,16	0,000
Lag t-2	2,44	0,015	Lag t-2	-3,08	0,002	Lag t-2	-1,52	0,128
DJCA			*DJCA*			*OMXHC*		
Lag t-1	14,22	0,000	Lag t-1	17,87	0,000	Lag t-1	14,87	0,000
Lag t-2	-1,05	0,292	Lag t-2	1,04	0,299	Lag t-2	-0,46	0,648

Results for Granger causality test are summed up in table 5.8. First column indicates the studied index and second column the other part of the equation. Null hypothesis test that can index in column 2 be excluded from the Granger-causality analysis. The last column holds the probability of the null hypothesis being rejected. The null hypothesis can be rejected in 95 % acceptance ratio, if probability value in the last column is between 0,000 and 0,050.

For example first row shows how OMXHC affects to Nikkei. Test analysis that can OMXHC index be completely excluded Nikkei's. In other words, does OMXHC explain Nikkei's daily return values? Probability for this is 0,000 and so OMXHC Granger causes Nikkei. On the third row is tested that can all tested indices be excluded from the test. The probability for this is also 0,000 so DJCA and OMXHC together explain Nikkei's daily return values.

It appears that the probability lies inside the acceptance region at 5% when all three indices are included in the test. These three indices together can explain the stock market movements. However, it can be also seen that there is 27,7 % probability that DJCA does not cause OMXHC alone. It is the only null hypothesis that can be accepted at 5 % acceptance region. We can accept the null hypothesis that Dow Jones Composite Average would alone cause changes of the OMXHC's daily returns. This may result from the fact DJCA includes more traditional and large cap companies, which differs from OMXHC that includes small and large companies that are listed in the Helsinki

Stock Exchange. The growth rate and volatility results that were introduced in the section 5.1 also show that DJCA's growth is steadier and isn't so sensitive to market movements.

Table 5.8 Granger causality for daily returns

Granger causality Wald tests

Equation	*Excluded*	*chi2*	*df*	*Prob > chi2*
Nikkkei	OMXHC	164,94	2	0,000
Nikkei	DJCA	7,73	2	0,021
Nikkei	ALL	166,49	4	0,000
OMXHC	Nikkei	10,34	2	0,006
OMXHC	DJCA dr	2,57	2	0,277
OMXHC	ALL	14,68	4	0,005
DJCA	Nikkei	8,88	2	0,012
DJCA	OMXHC dr	224,24	2	0,000
DJCA	ALL	269,16	4	0,000

6. CONCLUSIONS

This study examines the Granger causality of the stock exchanges and focuses on the Helsinki, New York and Tokyo Stock Exchanges. The causalities between various stock markets have been extensively investigated over a number of different stock markets and time horizons in earlier financial literature (i.a. Eun & Resnick 1988; Santti 2002; Hatemi-J & Roca 2004; Égert & Kocenda 2007). It has been discovered widely that there are comovements in stock prices but there has been variation of results on how strong the relationship is between different stock index pairs. Results have showed that there are some clusters that have stronger connections. Asprem (1989) reported a strong linkage between European continental markets but at the same time noticed Finnish market differed from other Nordic and European markets. Hatemi-J and Roca (2004) concluded in their study that countries which are associated through Chinese culture (China, Hong Kong, Singapore and Taiwan) had integrated and diversification within that group of markets may not be attractive. Although earlier literature supports the fact that there are comovements between stock markets, it can be argued that are domestic factors more dominant than impact of a foreign market. Hiraki and Maberly's (2000) study of the Japanese market supported the fact that movement in the Japanese stock market was more likely produced by institutional factors that are unique to Japan.

The empirical results in this paper demonstrate that there exist strong relationships among the selected stock markets. USA is dominant for all the markets but the Granger-causality is weaker than expected. It can be explained with the differences of the compared indices. Nikkei 225 and OMX Helsinki Cap include smaller companies and reflect better the overall market movements. Dow Jones Composite Average focuses more to larger companies which causes more moderate daily returns and weaker reactions to macroeconomic news. Comparison of the indices price development showed that Nikkei 225 and OMX Helsinki were more sensitive for sudden downswings and upswings, but Dow Jones Composite Average followed more the long time-period trend. Some other index from New York Exchange could have reflected better the overall market development and increased the reliability of the test results.

OMXHC differs from the other indices because it is weight limited index. Helsinki Stock Exchange is relatively small market place and bigger companies like Nokia control strongly the price development of the non-weight limited index. OMXHC limits Nokia's weight in the index and reflects more the overall market development. Data was collected from Thomson Financial DataStream and included daily close values for the three indices. Data with more daily observations would provide better possibility to study the length of the lag. Shorter interval between observations would improve the reliability of the results.

Results also indicate that Nikkei Granger-cause the other two indices and time-zone adjustments strengthen the causality among the three variables. Nikkei's impact to Helsinki was founded out to be even stronger than New York's. Asprem (1989) founded out in earlier study that there were significant positive relationships between the S&P 400 and the local European markets but there was one exception in results, Finland. These are in line with the findings in this paper. New York alone cannot explain the movements of the OMXHC. But it must be stated that none of the indices were completely apart from the two other indices. Nikkei and DJCA together can explain the movements of the OMXHC. There are clear causalities among the selected countries and upcoming returns can be predicted from the other markets close values. But information is available for everyone and it does not provide advantage for any investor and so it is not in conflict with efficient market hypothesis. It can be stated that market movements cannot be predicted with help of just one stock index. Comovement predictions require several indices in order to achieve better and more trustworthy results.

It should be noted that comovements in the stock markets have increased but still there are big differences in the performance of different stock indices. DJCA, Nikkei and OMXHC were selected to reflect the overall market development, but there were huge differences in the growth rate and annualized volatility among the indices during the analyzed time period. All the stock indices had strong comovements and causalities but still the difference between biggest (OMXHC) and smallest (Nikkei) growth rate was almost 8%. It can be concluded that national stock markets performance vary widely and factors that are unique for the nations have still impact to the overall performance. Findings are parallel with the Hiraki and Maberly's (2000) findings. Their results indicated that daily returns in the Japan market were more likely produced by institutional factors that are unique to Japan. Although, causalities among the three countries exist, the institutional factors cannot be fully excluded from the examination. Hatemi-J and Roca (2004) pointed out that connections among the different stock markets have increased over the time and most likely the causalities among the markets will increase, but local factors will continue to affect the overall performance also in the future.

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8. APPENDICES

Appendix 1: Augmented Dickey-Fuller test for unit root

Nikkei 225 daily returns

Augmented Dickey-Fuller test for unit root Number of obs = 2345

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-28.274	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = 0.0000

D.NIKTUOTTO	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
NIKTUOTTO						
L1.	-1.033235	.036543	-28.27	0.000	-1.104895	-.9615749
LD.	.0114113	.0295358	0.39	0.699	-.0465078	.0693304
L2D.	-.0093274	.0206561	-0.45	0.652	-.0498336	.0311787
_trend	1.61e-07	4.05e-07	0.40	0.691	-6.34e-07	9.56e-07
_cons	-.0000401	.0005494	-0.07	0.942	-.0011176	.0010373

DJCA daily returns

Augmented Dickey-Fuller test for unit root Number of obs = 2345

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-27.754	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = 0.0000

D.OMXTUOTTO	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
OMXTUOTTO						
L1.	-.9623217	.0346729	-27.75	0.000	-1.030315	-.8943288
LD.	.0026663	.028602	0.09	0.926	-.0534216	.0587543
L2D.	.0118496	.020636	0.57	0.566	-.0286172	.0523165
_trend	2.82e-07	3.62e-07	0.78	0.436	-4.27e-07	9.91e-07
_cons	-.0000315	.0004902	-0.06	0.949	-.0009928	.0009298

OMXHC daily returns

Augmented Dickey-Fuller test for unit root Number of obs = 2345

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-27.944	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = 0.0000

D.DJTUOTTO	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
DJTUOTTO						
L1.	-1.01968	.0364903	-27.94	0.000	-1.091237	-.9481237
LD.	.0042086	.0294681	0.14	0.886	-.0535777	.0619949
L2D.	-.0208969	.0206799	-1.01	0.312	-.0614497	.019656
_trend	2.10e-07	3.11e-07	0.67	0.500	-4.00e-07	8.19e-07
_cons	-7.44e-06	.0004211	-0.02	0.986	-.0008332	.0008183

Nikkei 225 relative values

Augmented Dickey-Fuller test for unit root Number of obs = 2345

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-1.241	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = 0.9017

D.NIK100	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
NIK100						
L1.	-.0014165	.0011413	-1.24	0.215	-.0036546	.0008217
LD.	-.0168455	.0206487	-0.82	0.415	-.0573372	.0236462
L2D.	-.0093136	.0206577	-0.45	0.652	-.0498229	.0311956
_trend	.000012	.0000395	0.30	0.761	-.0000653	.0000894
_cons	.1307811	.1247334	1.05	0.295	-.1138184	.3753807

DJCA relative values

Augmented Dickey-Fuller test for unit root   Number of obs = 2345

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-1.043	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = 0.9380

D.OMX100	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
OMX100						
L1.	-.0010494	.001006	-1.04	0.297	-.0030222	.0009233
LD.	.0322026	.0206542	1.56	0.119	-.0082997	.072705
L2D.	.0029653	.0206559	0.14	0.886	-.0375405	.0434711
_trend	.0000681	.000053	1.28	0.199	-.0000358	.000172
_cons	.0812212	.113927	0.71	0.476	-.142187	.3046295

OMXHC relative values

Augmented Dickey-Fuller test for unit root   Number of obs = 2345

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(t)	-1.502	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = 0.8285

D.DJ100	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
DJ100						
L1.	-.0022275	.0014831	-1.50	0.133	-.0051359	.0006809
LD.	-.0201021	.0206728	-0.97	0.331	-.060641	.0204369
L2D.	-.0352373	.0206719	-1.70	0.088	-.0757744	.0052998
_trend	.000073	.000044	1.66	0.097	-.0000133	.0001592
_cons	.1907144	.1421137	1.34	0.180	-.0879674	.4693963

Appendix 2: Test for cointegration

Daily returns

Johansen tests for cointegration

Trend: constant   Number of obs = 2346

Sample: 04jan1960 - 06jun1966   Lags = 2

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value	1% critical value
0	12	20306.628		3078.0315	29.68	35.65
1	17	20903.666	0.39889	1883.9563	15.41	20.04
2	20	21443.608	0.36891	804.0721	3.76	6.65
3	21	21845.644	0.29018			

Appendix 3: Vector autoregression and Granger causality tests

Vector autoregression

Sample: 04jan1960 - 06jun1966		No. of obs	= 2346
Log likelihood	= -11321.05	AIC	= 9.669268
FPE	= 3.176045	HQIC	= 9.688049
Det(Sigma_ml)	= 3.119691	SBIC	= 9.720832

Equation	Parms	RMSE	R-sq	chi2	P>chi2
NIK100	7	1.1985	0.9974	895731.6	0.0000
OMX100	7	1.44818	0.9984	1427042	0.0000
DJ100	7	1.09867	0.9970	786623.5	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
NIK100						
NIK100						
L1.	.8970732	.0200913	44.65	0.000	.8576951	.9364514
L2.	.1005967	.020105	5.00	0.000	.0611917	.1400017
OMX100						
L1.	.15593	.0174918	8.91	0.000	.1216467	.1902133
L2.	-.1556399	.0174678	-8.91	0.000	-.1898761	-.1214037
DJ100						
L1.	.3463681	.0233626	14.83	0.000	.3005782	.392158
L2.	-.3455234	.0233969	-14.77	0.000	-.3913804	-.2996664
_cons	.0887462	.1936196	0.46	0.647	-.2907413	.4682336
OMX100						
NIK100						
L1.	-.0918099	.0242768	-3.78	0.000	-.1393915	-.0442282
L2.	.0958176	.0242934	3.94	0.000	.0482034	.1434318
OMX100						
L1.	.9603398	.0211358	45.44	0.000	.9189144	1.001765
L2.	.0335889	.0211068	1.59	0.112	-.0077796	.0749575
DJ100						
L1.	.4819774	.0282297	17.07	0.000	.4266482	.5373065
L2.	-.4751969	.0282711	-16.81	0.000	-.5306072	-.4197866
_cons	-.3909556	.2339558	-1.67	0.095	-.8495005	.0675893
DJ100						
NIK100						
L1.	-.0302055	.0184177	-1.64	0.101	-.0663035	.0058926
L2.	.028985	.0184303	1.57	0.116	-.0071377	.0651076
OMX100						
L1.	-.0279233	.0160348	-1.74	0.082	-.0593509	.0035043
L2.	.030358	.0160128	1.90	0.058	-.0010264	.0617425
DJ100						
L1.	.9926521	.0214166	46.35	0.000	.9506764	1.034628
L2.	.003797	.021448	0.18	0.859	-.0382402	.0458342
_cons	.2472902	.1774915	1.39	0.164	-.1005868	.5951671

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
NIK100	OMX100	79.713	2	0.000
NIK100	DJ100	219.96	2	0.000
NIK100	ALL	393.01	4	0.000
OMX100	NIK100	17.785	2	0.000
OMX100	DJ100	292.95	2	0.000
OMX100	ALL	307.17	4	0.000
DJ100	NIK100	3.0727	2	0.215
DJ100	OMX100	4.9987	2	0.082
DJ100	ALL	10.238	4	0.037

Vector autoregression

```
Sample:  04jan1960 - 06jun1966                  No. of obs      =       2346
Log likelihood =  21845.64                      AIC             =  -18.60583
FPE            =  1.67e-12                      HQIC            =  -18.58705
Det(Sigma_ml)  =  1.64e-12                      SBIC            =  -18.55427
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
NIKTUOTTO	7	.012334	0.1410	385.0257	0.0000
OMXTUOTTO	7	.011109	0.1264	339.3032	0.0000
DJTUOTTO	7	.010169	0.0040	9.405508	0.1520

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
NIKTUOTTO						
NIKTUOTTO						
L1.	-.1175873	.0212344	-5.54	0.000	-.1592059	-.0759687
L2.	-.0124292	.020314	-0.61	0.541	-.0522439	.0273854
OMXTUOTTO						
L1.	.2110744	.0246136	8.58	0.000	.1628327	.2593162
L2.	.0583148	.0238841	2.44	0.015	.0115029	.1051267
DJTUOTTO						
L1.	.3753265	.0263984	14.22	0.000	.3235866	.4270664
L2.	-.0302154	.0286536	-1.05	0.292	-.0863755	.0259446
_cons	-.0000213	.0002545	-0.08	0.933	-.0005201	.0004775
OMXTUOTTO						
NIKTUOTTO						
L1.	-.0830635	.0191261	-4.34	0.000	-.12055	-.0455769
L2.	-.0144031	.0182971	-0.79	0.431	-.0502649	.0214586
OMXTUOTTO						
L1.	-.0468695	.0221699	-2.11	0.035	-.0903216	-.0034173
L2.	.0440947	.0215128	2.05	0.040	.0019305	.0862589
DJTUOTTO						
L1.	.4249288	.0237775	17.87	0.000	.3783258	.4715317
L2.	.0268282	.0258088	1.04	0.299	-.0237561	.0774124
_cons	.0002331	.0002292	1.02	0.309	-.0002162	.0006824
DJTUOTTO						
NIKTUOTTO						
L1.	-.0371861	.0175085	-2.12	0.034	-.0715022	-.0028701
L2.	.01	.0167496	0.60	0.550	-.0228287	.0428287

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
OMXTUOTTO						
L1.	-.0099908	.0202948	-0.49	0.623	-.0497679	.0297863
L2.	.0224765	.0196933	1.14	0.254	-.0161216	.0610746
DJTUOTTO						
L1.	-.0051793	.0217664	-0.24	0.812	-.0478407	.0374821
L2.	-.0143	.0236259	-0.61	0.545	-.060606	.032006
_cons	.0002373	.0002098	1.13	0.258	-.000174	.0006486

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
NIKTUOTTO	OMXTUOTTO	76.835	2	0.000
NIKTUOTTO	DJTUOTTO	210.46	2	0.000
NIKTUOTTO	ALL	382.58	4	0.000
OMXTUOTTO	NIKTUOTTO	18.999	2	0.000
OMXTUOTTO	DJTUOTTO	320.92	2	0.000
OMXTUOTTO	ALL	334.62	4	0.000
DJTUOTTO	NIKTUOTTO	5.1591	2	0.076
DJTUOTTO	OMXTUOTTO	1.6365	2	0.441
DJTUOTTO	ALL	7.3481	4	0.119

Nikkei 225 values moved up by one (t=>t-1 t-1=t-2)

Vector autoregression

```
Sample:  04jan1960 - 05jun1966                  No. of obs      =      2345
Log likelihood = -11315.53                      AIC             =  9.668678
FPE            =  3.174172                      HQIC            =  9.687466
Det(Sigma_ml)  =  3.117828                      SBIC            =  9.720261
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
NIK100	7	1.29261	0.9970	769728.1	0.0000
OMX100	7	1.41203	0.9984	1499395	0.0000
DJ100	7	1.09179	0.9971	795270.4	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
NIK100						
NIK100						
L1.	.9671815	.0221494	43.67	0.000	.9237695	1.010594
L2.	.0309134	.0221844	1.39	0.163	-.0125673	.0743941
OMX100						
L1.	.0012271	.0182877	0.07	0.947	-.0346161	.0370704
L2.	-.0011293	.0182239	-0.06	0.951	-.0368474	.0345888
DJ100						
L1.	.0503646	.0263272	1.91	0.056	-.0012358	.101965
L2.	-.049795	.0263607	-1.89	0.059	-.1014611	.0018711
_cons	.115124	.2087079	0.55	0.581	-.293936	.5241839
OMX100						
NIK100						
L1.	.2852922	.0241958	11.79	0.000	.2378693	.332715
L2.	-.2809803	.024234	-11.59	0.000	-.3284781	-.2334825
OMX100						
L1.	.8989484	.0199773	45.00	0.000	.8597937	.9381032

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
L2.	.0952469	.0199075	4.78	0.000	.0562288	.1342649
DJ100						
L1.	.3821243	.0287595	13.29	0.000	.3257567	.438492
L2.	-.3758738	.0287962	-13.05	0.000	-.4323133	-.3194343
_cons	-.3906668	.2279902	-1.71	0.087	-.8375194	.0561858
DJ100						
NIK100						
L1.	.1050979	.0187084	5.62	0.000	.0684303	.1417656
L2.	-.1062259	.0187379	-5.67	0.000	-.1429515	-.0695002
OMX100						
L1.	-.0487773	.0154466	-3.16	0.002	-.0790521	-.0185026
L2.	.0513055	.0153927	3.33	0.001	.0211364	.0814745
DJ100						
L1.	.9560699	.0222371	42.99	0.000	.912486	.9996538
L2.	.0402657	.0222654	1.81	0.071	-.0033738	.0839051
_cons	.2411628	.1762837	1.37	0.171	-.1043468	.5866725

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
NIK100	OMX100	.00592	2	0.997
NIK100	DJ100	3.6699	2	0.160
NIK100	ALL	4.0117	4	0.404
OMX100	NIK100	141.36	2	0.000
OMX100	DJ100	178.21	2	0.000
OMX100	ALL	445.78	4	0.000
DJ100	NIK100	32.215	2	0.000
DJ100	OMX100	12.608	2	0.002
DJ100	ALL	39.402	4	0.000

Vector autoregression

Sample: 04jan1960 - 05jun1966 — No. of obs = 2345
Log likelihood = 21837.85 — AIC = -18.60712
FPE = 1.67e-12 — HQIC = -18.58834
Det(Sigma_ml) = 1.64e-12 — SBIC = -18.55554

Equation	Parms	RMSE	R-sq	chi2	P>chi2
NIKTUOTTO	7	.013282	0.0019	4.560242	0.6013
OMXTUOTTO	7	.010813	0.1727	489.6041	0.0000
DJTUOTTO	7	.010089	0.0198	47.30672	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
NIKTUOTTO						
NIKTUOTTO						
L1.	-.034307	.022232	-1.54	0.123	-.077881	.009267
L2.	-.0330626	.0229146	-1.44	0.149	-.0779743	.0118492
OMXTUOTTO						
L1.	.026674	.0269007	0.99	0.321	-.0260505	.0793984
L2.	.0060241	.0245602	0.25	0.806	-.0421131	.0541613
DJTUOTTO						
L1.	.0259005	.0296257	0.87	0.382	-.0321647	.0839657
L2.	.0039962	.0308095	0.13	0.897	-.0563893	.0643816

_cons	.0001358	.0002741	0.50	0.620	-.0004014	.0006731
OMXTUOTTO						
NIKTUOTTO						
L1.	.207982	.0180988	11.49	0.000	.172509	.243455
L2.	-.0574701	.0186545	-3.08	0.002	-.0940322	-.020908
OMXTUOTTO						
L1.	-.090061	.0218995	-4.11	0.000	-.1329833	-.0471387
L2.	.0278189	.0199942	1.39	0.164	-.0113689	.0670068
DJTUOTTO						
L1.	.3470983	.0241179	14.39	0.000	.2998282	.3943684
L2.	.0319384	.0250816	1.27	0.203	-.0172207	.0810974
_cons	.0002376	.0002232	1.06	0.287	-.0001998	.000675
DJTUOTTO						
NIKTUOTTO						
L1.	.1040482	.0168876	6.16	0.000	.0709491	.1371474
L2.	-.0264953	.0174061	-1.52	0.128	-.0606106	.0076201
OMXTUOTTO						
L1.	-.0321476	.020434	-1.57	0.116	-.0721976	.0079023
L2.	.0206786	.0186562	1.11	0.268	-.0158868	.057244
DJTUOTTO						
L1.	-.0444555	.0225039	-1.98	0.048	-.0885623	-.0003486
L2.	-.0107284	.0234031	-0.46	0.647	-.0565977	.0351409
_cons	.0002441	.0002082	1.17	0.241	-.0001641	.0006522

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
NIKTUOTTO	OMXTUOTTO	1.0051	2	0.605
NIKTUOTTO	DJTUOTTO	.76511	2	0.682
NIKTUOTTO	ALL	2.4494	4	0.654
OMXTUOTTO	NIKTUOTTO	151.48	2	0.000
OMXTUOTTO	DJTUOTTO	207.29	2	0.000
OMXTUOTTO	ALL	484.66	4	0.000
DJTUOTTO	NIKTUOTTO	42.947	2	0.000
DJTUOTTO	OMXTUOTTO	4.0891	2	0.129
DJTUOTTO	ALL	45.159	4	0.000

Nikkei 225 and OMX Helsinki Cap values moved up by one (t=>t-1 t-1=t-2)

Vector autoregression

```
Sample:  04jan1960 - 05jun1966                    No. of obs      =      2345
Log likelihood = -11310.06                        AIC             =  9.664015
FPE            =  3.159404                        HQIC            =  9.682803
Det(Sigma_ml)  =  3.103322                        SBIC            =  9.715597
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
NIK100	7	1.25174	0.9972	820966.7	0.0000
OMX100	7	1.5343	0.9982	1270934	0.0000
DJ100	7	1.05128	0.9973	857926.3	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
NIK100						
NIK100						
L1.	.9067111	.021732	41.72	0.000	.8641172	.949305
L2.	.0903675	.021743	4.16	0.000	.0477519	.132983
OMX100						
L1.	.2272666	.0182175	12.48	0.000	.1915609	.2629722
L2.	-.2257568	.0182345	-12.38	0.000	-.2614958	-.1900178
DJ100						
L1.	-.0296852	.0257642	-1.15	0.249	-.0801821	.0208116
L2.	.0287507	.0257532	1.12	0.264	-.0217247	.0792261
_cons	.2061864	.2022329	1.02	0.308	-.1901828	.6025556
OMX100						
NIK100						
L1.	-.0846117	.0266376	-3.18	0.001	-.1368204	-.0324029
L2.	.0875215	.0266511	3.28	0.001	.0352862	.1397567
OMX100						
L1.	1.054933	.0223298	47.24	0.000	1.011167	1.098699
L2.	-.0590149	.0223507	-2.64	0.008	-.1028214	-.0152084
DJ100						
L1.	-.0081983	.03158	-0.26	0.795	-.0700939	.0536974
L2.	.0123065	.0315666	0.39	0.697	-.0495628	.0741759
_cons	-.2177811	.2478835	-0.88	0.380	-.7036239	.2680617
DJ100						
NIK100						
L1.	.0380347	.0182518	2.08	0.037	.0022619	.0738075
L2.	-.0400373	.018261	-2.19	0.028	-.0758282	-.0042464
OMX100						
L1.	.2143059	.0153001	14.01	0.000	.1843183	.2442936
L2.	-.2106597	.0153144	-13.76	0.000	-.2406753	-.180644
DJ100						
L1.	.8649625	.0216382	39.97	0.000	.8225524	.9073726
L2.	.130147	.021629	6.02	0.000	.0877549	.172539
_cons	.3217966	.1698466	1.89	0.058	-.0110967	.6546899

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
NIK100	OMX100	155.63	2	0.000
NIK100	DJ100	1.3908	2	0.499
NIK100	ALL	159.9	4	0.000
OMX100	NIK100	11.788	2	0.003
OMX100	DJ100	1.4299	2	0.489
OMX100	ALL	14.018	4	0.007
DJ100	NIK100	5.9385	2	0.051
DJ100	OMX100	197.81	2	0.000
DJ100	ALL	226.71	4	0.000

Vector autoregression

Sample:	04jan1960 - 05jun1966	No. of obs	= 2345
Log likelihood	= 21845.67	AIC	= -18.61379
FPE	= 1.65e-12	HQIC	= -18.59501
Det(Sigma_ml)	= 1.63e-12	SBIC	= -18.56221

Equation	Parms	RMSE	R-sq	chi2	P>chi2
NIKTUOTTO	7	.012841	0.0671	168.7451	0.0000
OMXTUOTTO	7	.011821	0.0080	18.81871	0.0045
DJTUOTTO	7	.009647	0.1038	271.5086	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
NIKTUOTTO						
NIKTUOTTO						
L1.	-.0997048	.0220721	-4.52	0.000	-.1429654	-.0564443
L2.	-.015464	.0218548	-0.71	0.479	-.0582986	.0273706
OMXTUOTTO						
L1.	.3138637	.0245138	12.80	0.000	.2658175	.3619099
L2.	.0552345	.0259799	2.13	0.033	.0043148	.1061543
DJTUOTTO						
L1.	-.0829343	.0298566	-2.78	0.005	-.1414523	-.0244164
L2.	-.0068753	.0288619	-0.24	0.812	-.0634435	.0496929
_cons	.0000605	.000265	0.23	0.819	-.0004589	.0005799
OMXTUOTTO						
NIKTUOTTO						
L1.	-.062303	.0203185	-3.07	0.002	-.1021266	-.0224795
L2.	-.0249071	.0201185	-1.24	0.216	-.0643385	.0145244
OMXTUOTTO						
L1.	.0684818	.0225662	3.03	0.002	.0242528	.1127108
L2.	.0310068	.0239159	1.30	0.195	-.0158674	.0778811
DJTUOTTO						
L1.	-.0277268	.0274846	-1.01	0.313	-.0815956	.0261419
L2.	.0292227	.0265688	1.10	0.271	-.0228513	.0812966
_cons	.0002908	.000244	1.19	0.233	-.0001873	.000769
DJTUOTTO						
NIKTUOTTO						
L1.	.0476694	.0165824	2.87	0.004	.0151684	.0801704
L2.	-.0086382	.0164192	-0.53	0.599	-.0408191	.0235428
OMXTUOTTO						
L1.	.2738557	.0184169	14.87	0.000	.2377593	.3099521
L2.	-.0089004	.0195183	-0.46	0.648	-.0471556	.0293548
DJTUOTTO						
L1.	-.1400252	.0224308	-6.24	0.000	-.1839888	-.0960615
L2.	-.015388	.0216835	-0.71	0.478	-.0578868	.0271109
_cons	.0001824	.0001991	0.92	0.359	-.0002078	.0005727

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
NIKTUOTTO	OMXTUOTTO	164.94	2	0.000
NIKTUOTTO	DJTUOTTO	7.7337	2	0.021
NIKTUOTTO	ALL	166.49	4	0.000
OMXTUOTTO	NIKTUOTTO	10.339	2	0.006
OMXTUOTTO	DJTUOTTO	2.569	2	0.277
OMXTUOTTO	ALL	14.676	4	0.005
DJTUOTTO	NIKTUOTTO	8.882	2	0.012
DJTUOTTO	OMXTUOTTO	224.24	2	0.000
DJTUOTTO	ALL	269.16	4	0.000